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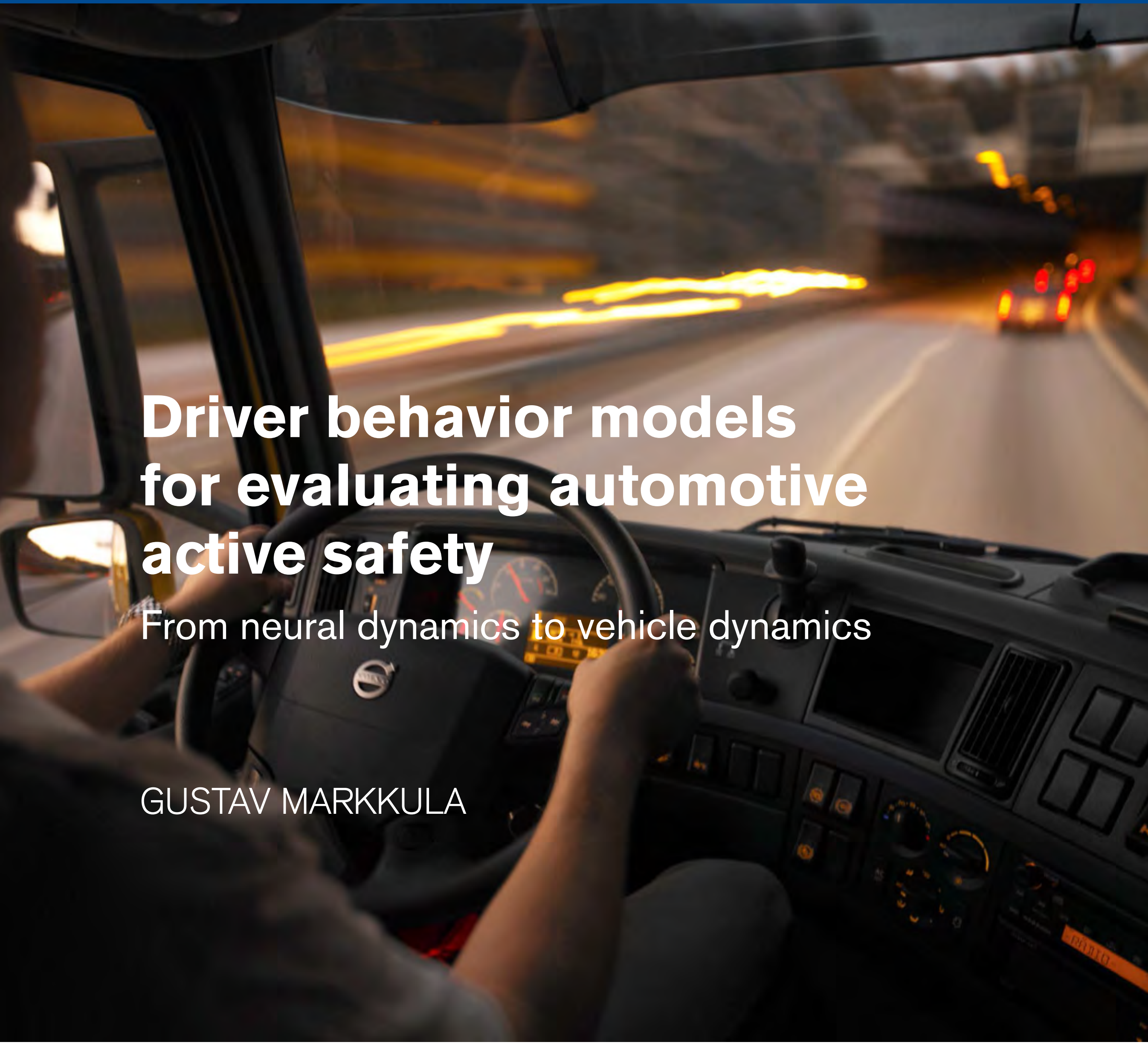

Driver behavior models for evaluating automotive active safety

From neural dynamics to vehicle dynamics

GUSTAV MARKKULA

Department of Applied Mechanics
CHALMERS UNIVERSITY OF TECHNOLOGY
Gothenburg, Sweden 2015

THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY IN MACHINE AND VEHICLE SYSTEMS

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Abstract

The main topic of this thesis is how to realistically model driver behavior in computer simulations of safety critical traffic events, an increasingly important tool for evaluating automotive active safety systems. By means of a comprehensive literature review, it was found that current driver models are generally poorly validated on relevant near-crash behavior data. Furthermore, competing models have often not been compared to one another in actual simulation.

An applied example, concerning heavy truck electronic stability control (ESC) on low-friction road surfaces (anti-skidding support), is used to illustrate the benefits of simulation-based system evaluation with a driver model, verified to reproduce human behavior. First, a data collection experiment was carried out in a moving-base driving simulator. Then, as a complement to conventional statistical analysis, a number of driver models were fitted to the observed steering behavior, and compared to one another. The best-fitting model was implemented in closed-loop simulation. This approach permitted the conclusion that heavy truck ESC provides a safety benefit in unexpected critical maneuvering, something which has not been previously demonstrated. Furthermore, ESC impact could be analyzed at the level of individual steering behaviors and scenarios, and this impact was found to range from negligible, when the simulated drivers managed well without the system, to large, when they did not. In severe skidding, ESC reduced maximum body slip in the simulations by 73 %, on average. Some specific ideas for improvements to the ESC system were identified as well. As a secondary applied example, an advanced emergency brake system (AEBS) is considered, and a partially novel approach is sketched for its evaluation in *what-if* resimulation of actual recorded crashes.

A number of new insights and hypotheses regarding driver behavior in near-crash situations are presented: When stabilizing a skidding vehicle, drivers were found to employ a rather simple and seemingly suboptimal yaw rate nulling strategy. Collision avoidance steering was found to be best described as an open-loop steering pulse of constant duration, regardless of amplitude. Furthermore, by analysis of data from test tracks as well as real-life crashes and near-crashes, it was found that detection of a collision threat, and also the timing of driver braking or steering in response to it, may be affected by a combination of situation kinematics and processes of neural evidence accumulation.

These ideas have been tied together into a modeling framework, describing driving control in general as constructed from intermittent, ballistic control adjustments. These, in turn, are based on overlearned sensorimotor heuristics, which allow near-optimal, vehicle-adapted performance in routine driving, but which may deteriorate into suboptimality in rarely experienced situations such as near-crashes.

Keywords: Driver models, control behavior, active safety, system evaluation, simulation

For Charlotte and X, my Papers 0 and VII.

Acknowledgments

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Call me a nerd, but for me, spending five years worth of my life on one, narrow subject has been an absolute privilege. Doing so would not have been possible, nor anywhere near as fruitful, had it not been for a large number of people providing me with their support. Many sincere and heartfelt thanks are therefore due:

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To you, Veronica. I could not have hoped for a better life companion.

To Charlotte: My book is done now, and it looks like I may be getting that hat soon.

Thesis

This thesis consists of a set of introductory chapters, and the following papers:

Paper I	G. Markkula, O. Benderius, K. Wolff, and M. Wahde. "Effects of experience and electronic stability control on low friction collision avoidance in a truck driving simulator". *Accident Analysis & Prevention* 50 (2013), pp. 1266–1277.
Paper II	O. Benderius, G. Markkula, K. Wolff, and M. Wahde. "Driver behaviour in unexpected critical events and in repeated exposures - a comparison". *European Transport Research Review* 6 (2014), pp. 51–60.
Paper III	Excerpt from: T. Victor, J. Bärgman, C.-N. Boda, M. Dozza, J. Engström, C. Flannagan, J. D. Lee, and G. Markkula. *Safer Glances, Driver Inattention, and Crash Risk: An Investigation Using the SHRP 2 Naturalistic Driving Study.* Phase II Final Report. Transportation Research Board of the National Academies, 2014.
Paper IV	G. Markkula, O. Benderius, K. Wolff, and M. Wahde. "A review of near-collision driver behavior models". *Human Factors* 54.6 (2012), pp. 1117–1143.
Paper V	G. Markkula, O. Benderius, and M. Wahde. "Comparing and validating models of driver steering behaviour in collision avoidance and vehicle stabilization". *Vehicle System Dynamics* 52.12 (2014), pp. 1658–1680.
Paper VI	G. Markkula. "Modeling driver control behavior in both routine and near-accident driving". *Proceedings of the Human Factors and Ergonomics Society Annual Meeting.* Vol. 58. Chicago, IL, Oct. 2014, pp. 879–883.

Other, related, publications by the author: [10, 11, 26, 34, 109, 113, 114]
Manuscript in preparation, cited in this thesis: [107]

Technical terms and abbreviations

Contents

Chapter 1
Introduction

A truck driver is taking her 30-ton vehicle down an arterial road, one which she knows well from almost daily passages during her fifteen years of professional experience. Traffic is flowing nicely, and there is just one more hour of work remaining before she can return home to her family. Suddenly, out of nowhere, our driver finds herself on a course for imminent, high-speed collision with the passenger car ahead, which is stopping for something, a traffic queue ahead, an animal passing on the road, or some obstacle blocking an intended exit from the road. Time freezes. The situation as such is clear, in all its minute detail: the distance separating truck and car, their current speeds and accelerations, how the two vehicles would respond to altered pedal or steering wheel inputs, the curvature of the road, the friction between asphalt and wheels. With all this knowledge, could we predict what will happen next? Will the truck driver crash into the rear of the passenger car, or will she brake quickly and strongly enough to stop behind it? Will she maybe reach the split-second decision to change lanes, and carry out a successful steering collision avoidance? Or will the specifics of her steering cause her to lose control over the truck, sending it skidding off the road? Crucially, what if the truck itself would have provided a warning to the driver, potentially making her realize the threat earlier? What if the truck would have applied automatic emergency braking as the collision drew nearer, or helped stabilize itself during skidding? Could such interventions have transformed a potentially fatal collision into nothing but a passing scare?

Any adult individual in modern society is well aware that road traffic occasionally leads to accidents, causing economic costs, injuries and sometimes even death. From a global or societal perspective, this is a major challenge. In 2010, 1.24 million people died in vehicle crashes [176], and current trends suggest that road traffic accidents will rise from being the ninth most common cause of death, worldwide, to a fifth place in 2030 [177]. Counting both fatalities and injuries, costs for crashes are estimated to amount to 1-3 % of countries' gross domestic products [178].

Furthermore, it is by now well established that driver behavior plays a major role in the causation of traffic accidents, in the form of for example inattention, excessive speeding, or inadequate evasive maneuvering [92, 156]. Based on such insights, recent accident prevention efforts by governments, industry, and academia, have placed a major emphasis on **active safety** technologies. These technologies provide warnings or control interventions with the aim of improving driver behavior or mitigating the effects of inadequate driver behavior, at the rare occurrences of a risk of, for example, vehicle instability, collision, or road departure [18, 68, 69]. Figure 1.1 introduces two active safety systems that will serve as recurring examples in this thesis: (i) **advanced**

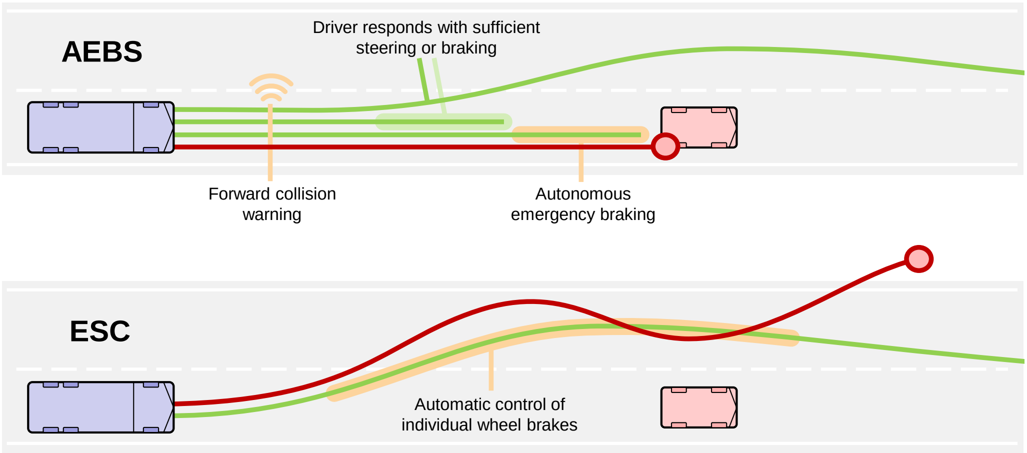


Figure 1.1: *Illustration of how two active safety systems could prevent crashes (the red trajectories ending in circles) in a rear-end conflict scenario. Top: Advanced emergency braking system (AEBS), providing a forward collision warning (e.g. light and sound) to prompt a braking or steering response from the driver, and autonomous emergency braking when collision is imminent [78, 161]. Bottom: Electronic stability control (ESC), maintaining yaw stability of the truck in spite of limited road friction, by applying individual wheel brakes to achieve the trajectory indicated by the driver's steering [153, 183].*

emergency braking system (AEBS), with sub-functionalities **forward collision warning (FCW)** and **emergency brake** and (ii) **electronic stability control (ESC)**.

As with any technology, active safety systems need **evaluation**, in order to determine to what extent they fulfill their intended purpose of reducing frequency or severity of crashes. System developers need to carry out **formative** evaluation [98], in order to be able to optimize a system before making it available on the market, and governments, insurance agencies, and vehicle-buyers need **summative** evaluations [98] of the end-product, to know what it is worth, whether to subsidize it, or if it should perhaps even be made mandatory by law.

The high-level, societal perspective on accidents clearly motivates the efforts invested in active safety systems, but there is another perspective that one can also take, equally valid, but with some possibly serious implications for the evaluation of these systems: *From the perspective of the individual driver*, accidents are extremely rare, and many drivers never crash at all during their lifetime. In the U.S., a police-reported crash with person injury occurs only once every 3 million kilometers of driving, and the same figure for Sweden is once every 5 million kilometers [127]. In other words, even if driver behavior can be put to blame for most crashes, the average driver is nevertheless impressively proficient at *not* crashing. The question thus arises: How does one evaluate a system when its performance depends crucially on the interplay with human behavior in situations that, from a first-person perspective, practically never occur?

The research work reported in this thesis aims, in general, to address this challenge by observing behavior in near-accident situations, and generalizing these observations into mathematical models of drivers' near-accident control over their vehicles. Such driver models can provide quantitative answers to "what happens next?"types of questions, such as those formulated in the opening of this chapter, and can therefore permit evaluation of active safety systems in computer simulation [6, 20]. This approach has the potential to avoid some problems, related to cost or validity, of alternative evaluation methods. In order to maintain a manageable scope of behaviors to study and model, this thesis focuses on the two active safety systems shown in Figure 1.1, specifically in the depicted rear-end collision type of conflict scenario.

The remainder of this chapter provides introductions to the general state of knowledge with regards to driver behavior in accident situations, and existing methods for evaluation of active safety. Then, the main research questions and the general research approach are introduced, an outline is provided for the rest of the thesis, and the author's contributions to the included papers are clarified.

1.1 Driver behavior and accident causation

How can one understand and describe behaviors such as, for example, those exhibited in Figure 1.1? On the conceptual level, there is a wealth of theories and models that propose different ways of how to best discuss driving, and sometimes also accidents [30, 34, 118, 151]. Here, a conceptual framework proposed by Ljung Aust and Engström [99], with the specific aim of supporting research in active safety, will be adopted.

In this framework, driving is viewed as **adaptive behavior**, the result of a balance between **motivation** to fulfill high-level goals, such as reaching the destination on time, and feelings of **discomfort** experienced in threatening situations. The driver and vehicle can together be regarded as a **joint driver-vehicle system (JDVS)** moving in the space of all possible states of the driver, vehicle, and the environment (a **DVE state space**), and the extent to which the JDVS can control the trajectory in this space is referred to as **situational control**. The region(s) in DVE space in which the driver does not experience any discomfort is called the **comfort zone**, and within this zone the driver is content with good-enough, **satisficing** [17, 146, 151] behavior. The comfort zone is typically entirely contained within the **safety zone**, the region(s) of DVE state space outside which situational control is reduced to a degree where a crash is inevitable. Fig. 1.2 provides an illustration of these ideas in an example scenario where a driver perceives a drop in road friction, and adapts by reducing vehicle speed, to stay within the comfort zone and keep a **safety margin** to the safety zone boundary.

In the framework of Ljung Aust and Engström, accidents are described, in general, as loss of situational control due to the driver failing to adapt properly to a current or changing DVE state. Furthermore, the main mechanisms which may, alone or in combination, lead to such adaptation failures are suggested to be (i) erroneous perception of the current safety zone boundary, (ii) overestimation of one's own ability, or that of the vehicle, (iii) an incorrect prediction of how a situation will develop over time, and (iv) rapidly occurring, unexpected events. Finally, the role of active safety systems is to help the driver adapt to DVE state changes, in order to ensure that situational control is

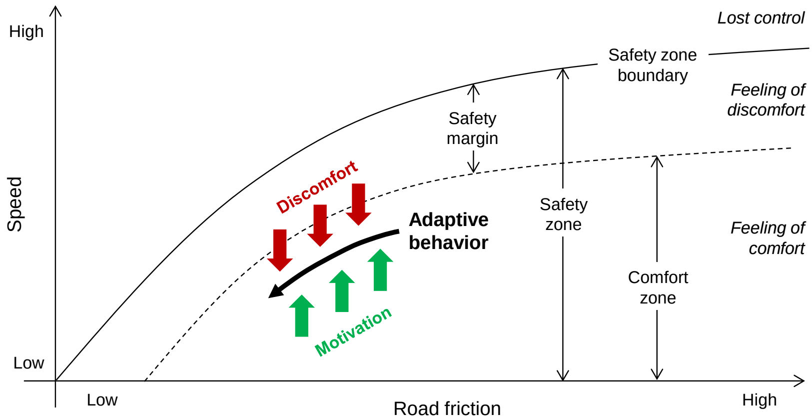


Figure 1.2: *Illustrations of key concepts of the conceptual framework of Ljung Aust and Engström, in a hypothetical scenario where a driver perceives a drop in road friction, and thus reduces vehicle speed to avoid experiencing feelings of discomfort. After [99].*

maintained.

This type of general framework is needed to structure thinking and writing. However, if one wants a more detailed description of driver behavior, for example to run computer simulations, there is a range of additional questions that require very specific answers. What information on the current DVE state do drivers perceive and use when controlling their trajectory in DVE state space? How do they translate these sensory inputs to control actions, and how can this process be described mathematically? Another phenomenon that cannot be neglected at this level is **behavioral variability**, i.e. variations in behavior either between drivers, due to factors such as driving experience [25, 37, 86] or personality [154], or within a given driver depending on factors such as for example fatigue [4] or effort [31, 64].

There exists a wide range of detailed, simulation-ready models, providing different answers to the questions listed above, and some of these models also account to some degree for behavioral variability [61, 63, 131]. However, these models typically address routine driving, leaving one potential source of within-driver variability, highly relevant to this thesis, largely unexplored: the shift from routine driving to more critical situations. Here, driver behavior that occurs close to a possible crash will be referred to as **near-crash behavior**, typically characterized as different from routine driver behavior in a number of ways. For example, near-crashing drivers often exhibit very slow reactions, or no reactions at all, even to stimuli that would seem to motivate immediate reactions [60, 94, 170]. Furthermore, when reactions come, they may (in hindsight) seem improperly chosen, such as braking and colliding when a steering maneuver could have avoided the crash [3, 90], or may come in the form of overreactions [105, 175] or underreactions not utilizing the full performance capabilities of the vehicle [3, 81, 90]. Some of the main candidates for factors explaining such phenomena include a limited driver **expectancy** of the threatening situation, emotional **arousal**, as in fear or panic, a high **uncertainty** of how other road users will behave, and drivers having a very limited **experience** of severe maneuvering [19, 28, 60, 90].

Does this mean that models of near-crash behavior ought to be fundamentally different from non-emergency models? If yes, must evaluation of active safety systems consider not only behavioral variability in general, but also specficially factors such as expectancy, fear, uncertainty, and inexperience?

1.2 Evaluation of active safety functions

Arguably, the only way of evaluating active safety that is completely valid, from a driver behavior perspective, is to exclusively consider **naturalistic** situations, as in real critical situations, in real traffic. The most straightforward approach to doing so is to use statistics from e.g. accident databases or insurance claims records: After market introduction of a safety system, one may simply wait for a sufficient number of accidents to occur, and then investigate whether system-equipped vehicles are involved in fewer or less severe crashes than other vehicles. From passenger car statistics, ESC has been shown to prevent about 40 % of all crashes involving loss of control [67], and AEBS has been found to reduce property damage insurance claims by 10-14 % [68].

A related approach, yielding more rich data sets, thus allowing deeper insights into system-related driver behavior, is to conduct **field operational tests (FOTs)**, in which logging equipment is installed in fleets of vehicles, operated by regular drivers during extended periods of time. The author is not aware of any FOTs targeting ESC, but both for passenger cars and trucks, FOTs have demonstrated benefits of the FCW component of AEBS, in terms of faster reactions to conflicts [8] or fewer harsh braking incidents [74]. One clear limitation with this type of approach is the high cost. In addition, a necessary limitation of any naturalistic evaluation method is the requirement of having system hardware and software mature enough for prolonged use by end-users. In practice, this means that naturalistic evaluation will be more summative than formative in character.

In order to perform formative evaluation, system developers often turn to **test tracks**, where early prototypes can be subjected to controlled testing. For ESC, this type of evaluation generally has an experienced test driver follow a predefined path, or a driving robot carry out predetermined steering maneuvers in **open-loop** fashion [97, 158], as opposed to **closed-loop** maneuvering, where the outcome of past control is continuously taken into account to update later control. For AEBS, the vehicle under evaluation is typically set on a collision course with a moving or static obstacle, and sometimes a driver response to FCW is emulated by a driving robot applying open-loop braking [5, 7, 39]. An important benefit of evaluating on the test track is the relatively high **repeatability**, allowing efficient comparison of the outcome with and without a system, between alternative versions of a system, or between different makes and models of system-equipped vehicles. Consequently, this is also the approach used for type approval and safety rating of on-market ESC and AEBS [38–40, 158].

However, it should be acknowledged that much realism in driver behavior may have been sacrificed in order to reach this repeatability. It seems likely that driving robots executing predetermined pedal or steering wheel movements, or experienced test drivers following cone tracks, produce a much less varied range of behaviors than normal drivers in near-crash situations. In some cases, it could even remain to be proven that the specific range of behaviors studied on the test track is at all represented in real traffic. This is not to say that active safety systems evaluated on the test track do not provide real benefits for traffic safety (as mentioned above, accident statistics show that they do), but it could for example mean that a better performance of system A than system B in a test track evaluation does not guarantee that system A will provide the greater benefit in reality.

One means of obtaining more realistic driver behavior is to try to stage unexpected events on a test track [42, 78]. Another is to use **driving simulators**. In simulators, a sample from a population of normal drivers can be safely subjected to near-crash scenarios that are, if not entirely unexpected and realistic, at least more so than typical test track scenarios. Especially FCW has been extensively researched in this way, from a large number of different perspectives [2, 27, 93, 96, 100, 116], but also the emergency braking component of AEBS [120], as well as ESC [26, 115, 130].

In general, these simulator studies have been able to demonstrate beneficial safety effects of the tested systems, even under the increased variability in behaviors exhibited by surprised drivers. However, the higher experimental validity comes at a price: In order to maintain sufficient statistical power despite behavioral variability, simulator studies typically have to address a more limited range of experimental conditions (e.g. number of traffic scenario variations, number of system variations, etc.) than test track studies, and need a larger number of measurements per condition. Furthermore, driver expectancies for critical situations typically increase with exposure, making it difficult to validly record near-crash behavior more than once per subject [32]. In sum, cost is definitely a concern also for simulator-based system evaluation.

Possibly the most cost-efficient evaluation method of all, then, would be to exclude the human drivers altogether, and replace them with **mathematical models of human behavior**. Using driver behavior models, relevant scenarios can be simulated with even greater repeatability than on the test track, as many times as wanted. Table 1.1 provides a summary comparison of the various evaluation methods introduced in this section.

At the outset of the research project behind this thesis, ESC had been subjected to evaluation in computer simulation, but only as simulated reproductions of test track evaluations [75, 87, 153, 169]. Active safety evaluations that are instead based on more realistic near-crash simulations have started to become available mainly in the last five years [6, 29, 36, 51, 83, 84, 119, 126, 142, 173, 174], although some earlier examples exist, mainly concerning FCW [20, 45, 93, 150]. One important milestone in this area was the National Highway Traffic Safety Administration (NHTSA) Advanced Crash Avoidance Technologies (ACAT) program, with the first projects ending around 2010; a main target for ACAT was to develop a U.S. national level benefits estimation methodology, with simulation as a key component [22, 48]. Indeed, as ever growing quantities of actual logged, time-course data from accidents are becoming available, from large-scale naturalistic studies [159] or widely deployed systems for monitoring or event recording [35, 85], **what-if** resimulation, where one estimates what impact an active safety system would have had on a set of actual crashes, seems like a very attractive approach for active safety evaluation.

More will be said about these existing approaches to simulation-based evaluation

Table 1.1: Comparison of alternative methods for evaluating active safety systems. The main purpose is to highlight differences between methods; specific evaluations may depart significantly from the typical characterizations provided here.

System evaluation method	Combinations of system and scenario variations	Approximate cost, nearest power of 10	Development phase	Realism of driver behavior
Analysis of existing accident data (featuring the system)	One system alternative; no experimental control over scenarios	$\approx$ 10 k€	Summative	Full
Field operational test	-”-	$\approx$ 1 000 k€	Mainly summative	Full
Test track evaluation	$\approx$ 10	$\approx$ 10 k€	Formative and summative	Low
Driving simulator experiment	$\approx$ 4	$\approx$ 100 k€	-”-	High
Computer simulation	$>$ 1 000	$\approx$ 10 k€*	-”-	Depends on the driver model

* Assuming that no major effort is needed to develop e.g. driver models, traffic scenarios to simulate, etc.

later in this thesis. For now, what about the driver models? After all, as pointed out in Table 1.1, the realism of a simulation is limited by the realism of its models. In the previous simulation-based evaluations of FCW and AEBS cited above, the driver model has recurrently been of the simple, open-loop type that could easily be implemented in a driving robot, e.g. applying a constant deceleration d a reaction time T_{R} after warning, two parameters which may be either fixed or drawn from probability distributions. Is this type of model close enough to reality to produce acceptably correct evaluation results? For example, several studies have noted that FCW may redirect a driver's off-road eye gaze back to the road, but the actual control responses seem to come rather in response to the rear-end situation than to the warning itself [93, 100, 167]. This could point to a need for more situation-dependent driver models. In the previous simulations of ESC in realistic near-crash scenarios, there is one example of what seems to be open-loop modeling [29] and one example of closed-loop modeling [119], however in the latter case using a model which does not seem to have been validated on near-crash behavior data [95]. Again, do these models capture enough of what human drivers do in real critical situations for the evaluations to be of any value? Such questions are at the very core of what is being addressed in this thesis.

1.3 Research objectives and thesis structure

As previously mentioned, the general aim of the present research work has been to identify models that accurately describe near-crash driver behavior, in order to ensure validity of simulation-based active safety evaluations.

However, rather than aiming for models that would be applicable across many different traffic scenarios and active safety systems, modeling has been constrained to two specific

use cases for driver-vehicle-environment (DVE) simulation. These were chosen by considering both the applied relevance for the involved industrial project partners, and the estimated potential for making a valuable scientific contribution to driver modeling.

In **the ESC use case**, driver models and simulations have been developed to answer the following research questions:

(A) Does heavy truck ESC provide a safety benefit for normal drivers in realistic near-crash maneuvering? Accident statistics provide strong evidence for the safety benefit of passenger car ESC [67], but similar investigations have not been possible yet for trucks, because of limited market penetration [175]. Also in simulator studies, benefits of passenger car ESC have been proven [115, 130], but the only similar study on trucks was unable to find a statistically significant effect, possibly due to a too small sample size [26].

(B) Is ESC equally useful for all drivers in realistic near-crash maneuvering? A potential advantage of driver modeling is the possibility of isolating and studying behavior of individual drivers [37, 182], for example to understand whether ESC should work differently for different drivers. This research question was further motivated by anecdotal reports of ESC sometimes being perceived to interfere with routine driving; could indications of such interference be found in critical situations?

In **the AEBS use case**, the target has been to develop driver models and simulations for what-if evaluation of heavy truck AEBS on actual logged time-course data from rear-end crashes. In other words, the main research question has been:

(C) For a given recorded rear-end crash, what would have happened if AEBS had been present? A full answer to this question requires both a methodology for what-if evaluation and good models of many aspects of driver behavior, and this thesis will only partially address these needs. A sketch of an evaluation method will be provided, and one specific model-related question will be explored in some detail:

(D) Is the timing of drivers' defensive maneuvers in rear-end conflicts dependent on the specific situation kinematics, and, if so, how can this dependence be modeled? As mentioned above, existing simulation-based evaluations of AEBS-like systems have posited kinematics-independent distributions, but several studies suggest that this is an insufficient account of driver behavior.

A three-step approach, also reflected in the structure of this thesis, has been adopted for both use cases:

1. **Measure human control behavior** in as relevant and realistic settings as possible (Chapter 2). This has involved one simulator experiment on ESC, and analysis of one naturalistic data set on rear-end crashes and near-crashes.

2. **Identify driver models** that can reproduce the observed control behavior (Chapter 3). Answering research question D is an obvious aim of this part of the process, but as we shall see, it is possible already at this stage to answer also question A.

3. **Implement and run simulations** that are required by the use cases (Chapter 4). This includes providing an answer to research question B, as well as a sketch of the envisioned approach for answering research question C.

Each of the Chapters 2 through 4 will first address the topic at hand from a general perspective, before presenting the specific efforts made in relation to the two use cases.

Finally, a secondary research aim has been to evaluate the possibility of generalizing the very delimited, use case-specific driver models into a more general modeling framework. This will be the topic of Chapter 5. Finally, in Chapter 6, conclusions will be made, and an outlook towards the future will be provided.

1.4 Contributions to the included papers

The author had the main responsibility for designing the ESC simulator study, providing the data set for Papers I, II, and V. The author also carried out the statistical analyses for Paper I, and wrote most of the text. For Paper II, the author collaborated with Benderius in determining the analysis approach, and assisted in the writing. The author collaborated with Victor, Bärgman, Engström, and Boda in extracting the data set and determining the analysis approach for Paper III, but did the analysis and writing himself. Preparations for and writing of the review in Paper IV was done in collaboration with Benderius, Wolff, and Wahde. The author generated the model-fitting results and analyses presented in Paper V, and wrote the paper. Paper VI was the author's product in its entirety.

Chapter 2
Measuring near-crash behavior

In the previous chapter, the main empirical approaches to human-in-the-loop evaluation of active safety were listed: naturalistic driving studies and controlled studies on test tracks or in simulators. These same approaches are useful also when collecting data for driver models, with the same considerations in terms of cost and driver behavior realism (Table 1.1). However, on closer inspection, the specific objective of supporting driver modeling, rather than evaluating a safety system, implies specific constraints for experimental design. The first section of this chapter will take a closer look at the concept of behavioral variability, to discuss how such variability is the very foundation for useful modeling while at the same time creating serious challenges for useful data collection. The remainder of the chapter will present the two specific data collection efforts covered in this thesis, together with results from initial, statistical analyses of the obtained data.

2.1 Aspects of behavioral variability

Human behavior is enormously variable, affected in myriad ways both by the state of the external world, observable to a third-party experimenter, and the internal states of the body and the brain, generally hidden from observation. Consider, again, the example rear-end situation sketched at the start of the previous chapter, and assume that one describes this specific DVE state, in detail, in the form of a very long vector $\boldsymbol{X_\Omega}$ of DVE parameters. Now, if one could twice very closely replicate the same traffic situation $\boldsymbol{X_\Omega}$, why not even down to the state of individual neurons in the truck driver's brain, one would expect that the truck driver would twice exhibit very similar control responses, pedal and steering wheel actions described in a vector $\boldsymbol{Y}$. If specific individual DVE parameters in $\boldsymbol{X_\Omega}$ were varied gradually, variations in $\boldsymbol{Y}$ would be expected. These variations in behavior could also be gradual, such as schematically illustrated in Fig. 2.1a, but there could just as well be more dramatic effects, for instance a small change in a headway distance causing a transition from a steering response to a braking response.

Driver modeling, as it is addressed in this thesis, amounts to finding mathematical expressions that describe relevant aspects of behavioral variability, in the form of mappings to $\boldsymbol{Y}$ from some subset $\boldsymbol{X} = \{X_1, X_2, ...\}$ of the DVE parameters in $\boldsymbol{X_\Omega}$. Consequently, experiments aiming to provide data for modeling should measure $\boldsymbol{Y}$ while, ideally, varying all of the DVE parameters in $\boldsymbol{X}$ independently. This ideal is not easy to live up to, but even if one can, there will now always be behavioral variability that the model can never account for, due to the dramatic simplification of passing from $\boldsymbol{X_\Omega}$ to $\boldsymbol{X}$. Fig. 2.1b illustrates this effect by showing a random sampling of the range of situations depicted in

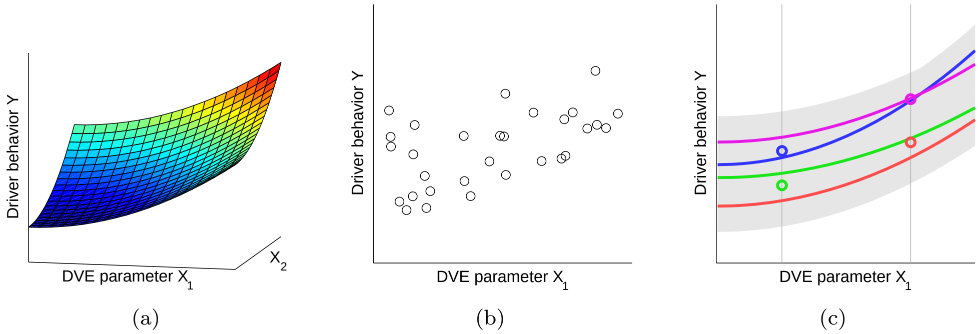


Figure 2.1: *Schematic illustrations of (a) a hypothetical effect of two Driver-Vehicle-Environment (DVE) parameters on a driver behavior variable Y, (b) behavioral variability from an uncontrolled DVE parameter, and (c) behavioral variability between different drivers (the four different curves), within each driver (the shaded areas around the curves), and one measurement from each driver (the rings) at one of two values of* X_1*.*

Fig. 2.1a, but without measuring X_2. In the rear-end collision example, X_1 could be **time to collision** (TTC, relative distance divided by relative speed), X_2 some quantification of how unexpected the rear-end conflict is to the truck driver, and Y could be the time until the truck driver starts braking. In a naturalistic setting, one may measure X_1, but will most probably have very vague notions, if any, of X_2. The variations in this **uncontrolled parameter** show up in Fig. 2.1b as behavioral variability, making the relationship between X_1 and Y more imprecise and difficult to discern.

Variability from uncontrolled parameters is the reason why non-naturalistic experiments on human behavior typically attempt to put all subjects in the exact same circumstances; if all drivers in a simulator study have had the same experiences from the start up until a sudden lead vehicle deceleration, chances are greater that X_2 in our example will be similar between measurements. However, even with perfect experimental control of this kind, other uncontrolled parameters related to the individual drivers will remain: **Between-subject variations** in some parameters will cause the mapping from X_1 to Y to differ between subjects, as exemplified by the four different curves in Fig. 2.1c. The shaded areas around these curves intend to illustrate how **within-subject variations** will also always arise, even if it is possible to sample the same $X_1 \rightarrow Y$ mapping several times. Furthermore, if the mapping is affected by some uncontrolled parameter that is influenced by measurement itself, such as the expectancy-related X_2 above, one may only be able to record once from each subject before behavior adapts and the mapping changes.

In cases where the only aim is to demonstrate that X_1 has some kind of impact on Y, the typical approach, illustrated by the rings in Fig. 2.1c, is to sample each driver at one of two distinct values of X_1, and test for a statistically significant difference. However, if the relationship between X_1 and Y must be described more completely in a driver model, a better coverage of X_1 is required. Additionally, if the aim is to elucidate between-driver differences in the $X_1 \rightarrow Y$ mapping, such as in the ESC use case considered in this thesis, one needs this coverage of X_1 also for each individual driver. How can this be achieved?

2.2 A simulator study on near-crash steering

In the ESC use case, the primary target for modeling was driver steering in the low-friction, rear-end type of scenario illustrated in the bottom panel of Fig. 1.1, where the driver first steers away from an impending collision and then stabilizes the vehicle on the road[1]. In other words, in each time step of an envisioned computer simulation, the driver model should be able to predict steering behavior $\boldsymbol{Y}$ as a function of a vector $\boldsymbol{X}$ of DVE parameters, for example regarding vehicle positions and speeds on the road, angles or rates of change of vehicle **yaw** (horizontal orientation), etc. Thus, here, a single recorded scenario of human steering passes through many DVE states $\boldsymbol{X}$, and therefore provides many measured pairs of $\boldsymbol{X}$ and $\boldsymbol{Y}$. However, since $\boldsymbol{X}$ is now multidimensional, a single scenario will still only provide a rather limited view of the complete $\boldsymbol{X} \rightarrow \boldsymbol{Y}$ mapping.

To gather enough data for a study of steering on the level of individual drivers, a 24-subject driving simulator study was designed, with two distinct stages. First, each driver was exposed, once, to a rear-end conflict scenario that was intended to be as unexpected as possible; a higher-speed lead vehicle overtaking the truck and continuing ahead for a while, before suddenly decelerating for no apparent reason [33]. Next, a novel experimental paradigm ensued, where repetitions of the same critical scenario were randomly interleaved with **catch trials**. In the catch trials, the lead vehicle decelerated only for a short while, such that braking alone was enough to avoid collision. By careful design of the exact scenario parameters, and by instructing the drivers only to perform steering avoidance when they deemed that this was necessary, repeated avoidance steering from a low TTC of between 2 and 3 seconds could be observed. As shown in Fig. 2.2, this was the most common point of avoidance steering also in the unexpected scenario. Crucially, this was a point from which collision avoidance and stabilization was challenging given the low road friction ($\mu = 0.25$), prompting frequent engagement of the ESC system, a software-in-the-loop implementation of an actual on-market system from Volvo Trucks. Full details on the simulator experiment are available in Paper I, and further insight into the process for arriving at the final experiment design is provided in the author's licentiate thesis [106].

In order to get some experimental control over individual differences, drivers were recruited into two groups: One low-experience group of drivers who had just obtained, or were just about to obtain, their truck driving licenses, and one high-experience group, with at least six years of professional truck driving experience. In the unexpected scenario, these groups differed markedly with respect to reaction times. While drivers in both groups typically followed the pattern of first braking, and then, in a majority of cases, also applying avoidance steering, the experienced drivers both braked and steered significantly earlier than the novice drivers, and the novice drivers collided significantly more often.

Fig. 2.3a shows the difference in steering reaction times, while also making another important point: Both the observed steering reaction times and the percentages of drivers who at all applied evasive steering (70 % and 82 %, in the low and high experience groups, respectively) could be explained by the same reaction time distributions. In existing

[1]This specific scenario was chosen both because it was deemed well-suited for simulation-based evaluation, and because avoidance maneuvers are known to be an important cause of heavy truck yaw instability [75]; a more detailed argument can be found in the author's licentiate thesis [106].

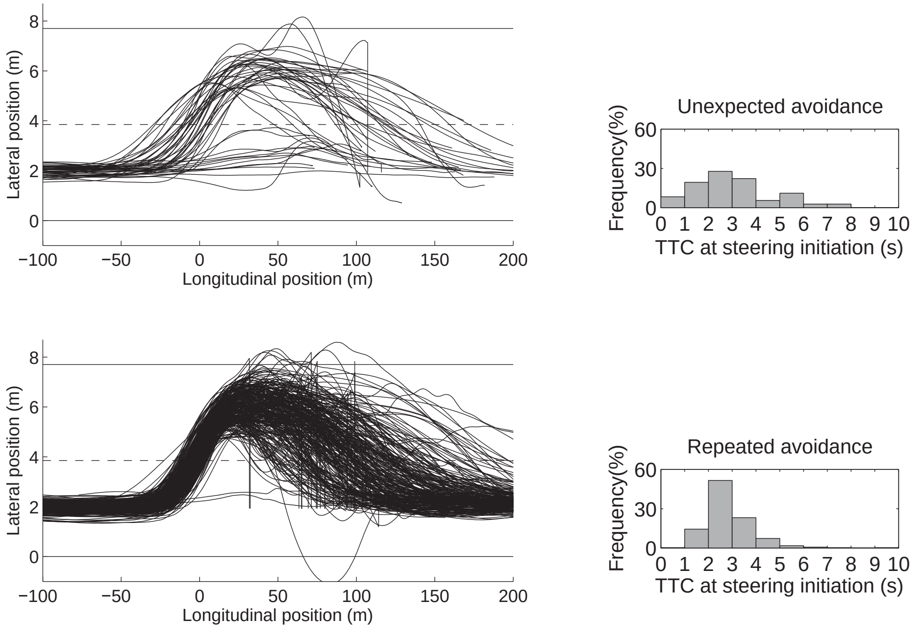


Figure 2.2: *Steering in the unexpected (top panels) and repeated (bottom panels) scenarios of the ESC simulator study. The panels on the left show the recorded truck trajectories, and the panels on the right show the distributions of time left to collision with the lead vehicle, when truck driver steering first exceeded* 15°. *Longitudinal position zero corresponds to the point at which the truck's front reached the rear of the lead vehicle. From Paper I.*

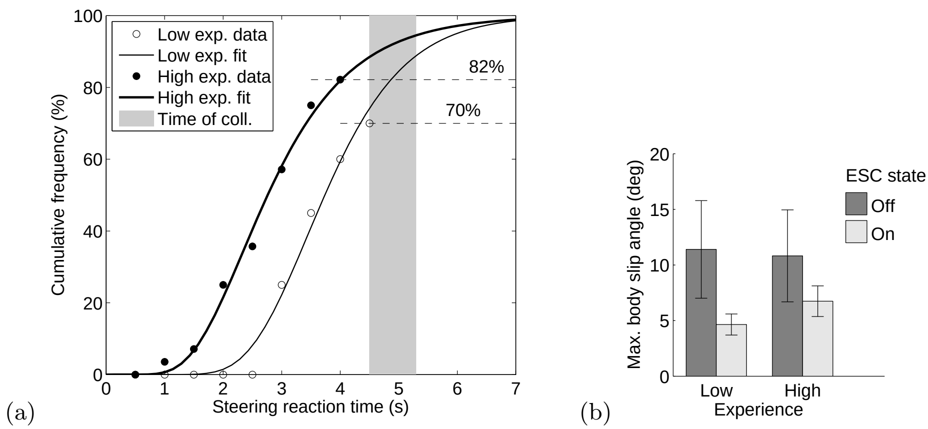


Figure 2.3: *(a) Cumulative steering reaction times after lead vehicle brake light onset in the unexpected scenario, up to the observed proportions of drivers applying steering, with least-squares fit of distributions (log-normal, as is often found suitable for reaction times [157]). The shaded region shows the time range within which all collisions occurred. (b) Effect of ESC on skidding, in the repeated scenario. Both panels from Paper I.*

models of driver behavior in rear-end conflicts, fixed probabilities have typically been adopted for the various basic avoidance maneuvers, e.g. "braking only" versus "braking and steering"[6, 150]. Fig. 2.3a instead suggests that reaction time distributions might be a more appropriate level of modeling, with probabilities of non-reaction arising naturally from reactions sometimes being too slow given the kinematics of the specific situation.

With regards to the ESC system, no significant effects of its presence were observed in the unexpected scenario. However, in the repeated scenario, ESC significantly reduced maximum **body slip angle** (Fig. 2.3b), i.e. how much the vehicle's front points away from the current movement direction, and frequency of **full control loss**, i.e. road departures and spin-arounds. One possible explanation for this difference in ESC impact is that there was simply not enough ESC-relevant data in the unexpected case. Indeed, there were only nine recordings of the unexpected scenario where steering was vigorous enough to potentially elicit ESC interventions, versus 217 such recordings of the repeated scenario. On the other hand, there is also the possibility that the drivers substantially changed their steering behavior (the $\boldsymbol{X} \to \boldsymbol{Y}$ mapping) between the two scenarios, and that the steering behavior in the unexpected scenario, presumably more realistic, was somehow less compatible with the ESC system. This possibility needs to be carefully considered, since the very idea behind the design of this experiment was that near-crash steering behavior might be reasonably conserved between unexpected and repeated measurement, such that driver models developed based on the repeated measurements might come reasonably close to behavior in realistic, unexpected scenarios.

Therefore, as reported in Paper II, statistical comparisons were carried out regarding steering behavior in the two scenarios, for a subset of eight drivers where such comparison was considered feasible, and for those parts of the scenario where suitable quantitative metrics could be readily defined. During collision avoidance and initial alignment with the left lane (see Fig. 2.4a), no statistically significant effects were found of scenario or repetition, on maximum angles or rates of steering (see example in Fig. 2.4b), or on **steering wheel reversal rate**, i.e. the frequency of small steering corrections [114]. For maximum angles and rates, traces of such behavior conservation were discernible also at the level of individual drivers; as shown in Fig. 2.4c, the two drivers who steered very fast during lane alignment in the unexpected scenario, did so also in the repeated scenario. However, this type of correlation between unexpected and repeated scenario behavior was not observed for the reversal rates (Fig. 2.4d). These were generally lower in repeated than in unexpected steering, consistent with previous proposals of increased experience and expectancy leading to steering that is more smooth and open-loop in character [37, 66].

In sum, the statistical analyses of the collected data allow the conclusions that ESC provided a benefit in the repeated scenario, and that there were more similarities than differences between unexpected and repeated steering, in the initial phases of collision avoidance and lane alignment. This goes some way towards suggesting that the ESC system should be helpful also in unexpected situations (research question A of this thesis), but the argument is weakened by the limited number of drivers considered in the behavior comparison, and the exclusion from comparison of the final stabilization phase of steering, more difficult to characterize with scalar metrics. With regards to individual differences in ESC benefit (research question B), the positive effect of ESC was potentially slightly

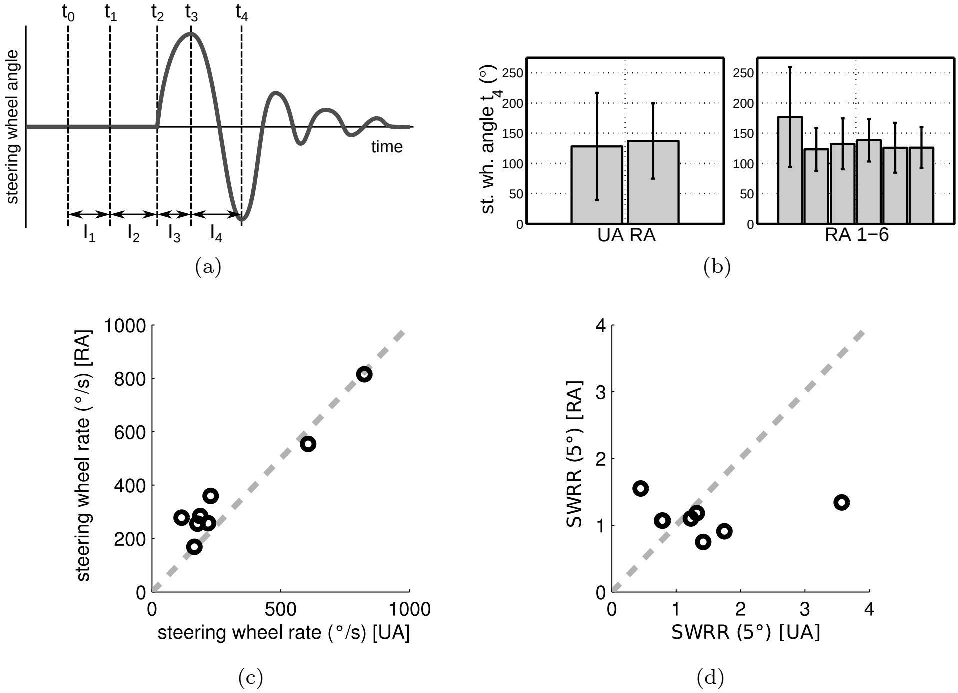


Figure 2.4: *(a) Phases of typical steering in the ESC study, with I_3 being collision avoidance, and I_4 alignment with the new lane. (b) Comparison of steering wheel angle at t_4, between unexpected and repeated avoidance (UA and RA), as well as over repetitions (RA 1-6). (c and d) Individual steering behavior, conserved between scenarios for steering wheel rate in segment I_4 (panel c), but not for steering wheel reversal rate in I_3 (panel d). All panels from Paper II.*

smaller for experienced drivers. When analyzing the two groups separately, the effect of ESC on full control loss did remain significant for both groups, but the effect on maximum body slip (Fig. 2.3b) was significant only for the novices. However, this type of group-level conclusion is still a far cry from saying anything meaningful about ESC in relation to *individuals*. These issues will be explored further in the coming chapters.

2.3 Near-crash response timing in naturalistic data

During the years 2011-2013, the world's largest naturalistic driving study to date was carried out in the U.S., as part of the **second Strategic Highway Research Program (SHRP 2)**. In this study, logging equipment was installed in the vehicles of more than 3000 volunteering drivers, generating a total of almost 80 million kilometers, or more than a hundred around-the-clock person-years, of recorded driving [15]. Paper III is an excerpt from the final report [159] of one of the associated analysis projects, dealing specifically with rear-end crashes and their relation to driver inattention, such as **visual distraction**

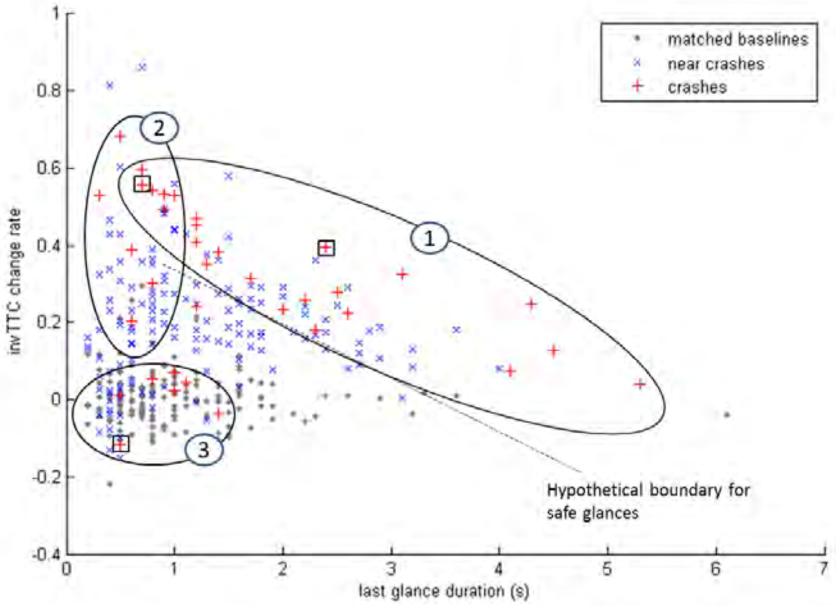


Figure 2.5: *Categorization of rear-end conflicts by duration of final off-road glance and average rate of change of inverse time to collision (TTC) during the glance. From [159]; note that this analysis is not part of the excerpt, from the same report, in Paper III.*

in the form of driver glances off the forward roadway. In this project, 46 rear-end crashes and 211 near-crashes were identified in the SHRP 2 data, both by means of automatic detection using various criteria, and other means such as incident reports from the drivers.

One important outcome of analyzing these events was a categorization of rear-end crashes, shown in Fig. 2.5, in terms of the interplay between visual distraction and the rear-end conflict itself. To interpret this figure, consider first the concept of **inverse TTC** (invTTC = 1/TTC). As a crash draws nearer, TTC decreases, and therefore invTTC increases, an increase which is faster closer to a crash, and faster for higher lead vehicle deceleration rates. In this sense, invTTC change rate is a measure of the kinematic severity of the rear-end conflict. Another reason for considering invTTC as a quantity is that it is plausibly available to the collision-avoiding human driver: For a given **optical angle** θ of an obstacle on the driver's retina, with time derivative $\dot{\theta}$, known as the **optical expansion** or **looming**, it is a well-known result [91] that $\mathrm{TTC} \approx \tau \equiv \theta/\dot{\theta}$, and $1/\tau = \dot{\theta}/\theta$ thus provides a visual estimate of invTTC[2]. It is also well established that there are dedicated neural circuits for looming detection in animal brains, implicated in for example collision-avoiding behaviors [46, 152]. Probable homologues of these looming-detection circuits have been identified in the human brain [14].

[2]It may be noted that $\dot{\theta}/\theta$ also has a direct interpretation in terms of the *relative* rate of expansion on the retina. For example, if an obstacle grows on one's retina by a third of its original size in 1 second, one knows that $1/\mathrm{TTC} \approx 1/3$, i.e. that a collision is 3 seconds away, regardless of other factors such as approach speed, distance, and object size.

Returning to Fig. 2.5, a majority of the extracted SHRP 2 crashes, labeled as Category 1, can now be understood as a perfect mismatch between glance duration and the nature of a rear-end conflict that arose during the glance: Very long off-road glances can cause crashes even in situations that are kinematically rather benign (low invTTC change rate), whereas in high-severity kinematics (high invTTC change rate), even very short glances might contribute to a crash. Category 2 crashes were found to be cases where the drivers glanced away briefly from an already established conflict, often in circumstances with reduced visibility. Category 3 crashes, finally, were cases where the conflict arose *after* the final glance, such that the glance itself may have been less involved in the causation of the crash.

In relation to research questions C and D of this thesis, the analysis presented in Paper III aimed to clarify what happened *after* the final off-road glance. Specifically, the timing of a manually annotated **physical reaction point**, defined as "the first visible reaction [of the driver to the lead vehicle, such as a] body movement, a change in facial expression etc.", was studied, as a proxy for timing of evasive braking or steering responses. Arguably, it would have been better to identify the onset of these maneuvers directly, but this was found to be difficult, partially because of limitations in data availability and quality. Furthermore, a well-defined onset may not always be present (see further Sect. 5.1). Reassuringly, however, follow-up analyses, not presented in Paper III or [159], have shown that peak decelerations were almost without exception reached *after* the physical reaction point, and in a majority of cases less than 0.5 s after it.

Even if the exact meaning and usefulness of the physical reaction point can be discussed, with the SHRP 2 data set there can be no questioning the validity of the observed behavior as such. This is a welcome contrast to the ESC study, where major efforts have been required for understanding the validity of the repeated-scenario behavior. However, as will become clear in the next chapter, the SHRP 2 data have other limitations, for example related to the issue of uncontrolled parameters, as introduced in Sect. 2.1, and to whether or not the selection of what events to include introduces biases in the data.

To summarize, there is probably no single perfect approach to measuring near-crash behavior. Controlled studies allow isolation of individual behavioral phenomena and mechanisms, and can therefore be highly useful in the development of models, whereas naturalistic data, unstructured but with full validity, provide the ultimate benchmark for model refutation or corroboration.

Chapter 3
Models of near-crash behavior

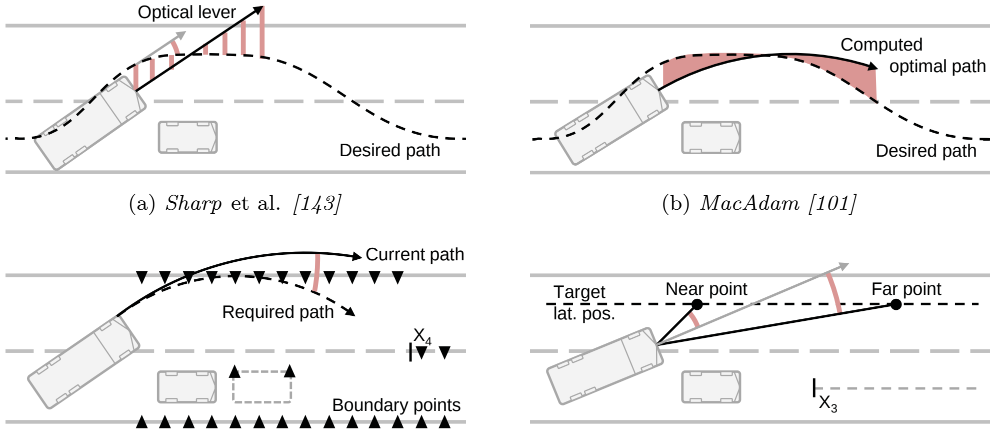
In its most general sense, a **model** in science is just "a simplified description of a system or process"[129], a very broad notion indeed. Consequently, the term **driver model** can be understood to mean a number of different things, for instance a **conceptual model** of driver behavior, like the framework by Ljung Aust and Engström outlined in Chapter 1. As clarified in Chapter 2, models to be used in evaluation of active safety typically need to be more quantitative in nature, mapping DVE states to mathematical descriptions of driver control behavior. This mapping can take the form of a **statistical model**, for example providing probability distributions for some limited aspect of control behavior, such as reaction times, in one or more DVE states. For full applicability, models should be able to close the control loop needed for computer simulation, by specifying momentary control actions as a function of momentary or previous DVE states, as was sketched for the ESC use case in Sect. 2.2. Models meeting this requirement can be referred to as **process models** [141] of driving behavior.

There is a wealth of alternative approaches to such process modeling, and the first section of this chapter provides a brief inventory. The three remaining sections describe (i) a comparison of candidate process models for the ESC use case, (ii) how a few of these were used to further clarify the ESC simulator study's validity, and (iii) a model of response timing in situations with risk of rear-end collision, such as observed in SHRP 2.

3.1 Understanding the alternatives

At the outset of this research project, it was clear that many process models of driving control behavior had already been proposed (see e.g. [131]), but it was less clear how much of this previous work had targeted behavior in more critical situations. Therefore, an extensive literature search was carried out, considering more than 5000 literature database search hits from the years 2000 to 2010. The result was a collection of more than 60 identified instances of near-crash behavior simulation, reviewed in Paper IV. Most of these previous simulation efforts also proposed their own specific driver models (in many cases this was the main research objective), either completely novel or as modifications of existing models. However, some recurring themes in modeling could be discerned.

A common type of very simple driver model, alluded to already in Chapter 1, could be referred to as a **delayed open-loop maneuver** model: A reaction time T_R after some event, e.g. a brake light onset or a driver glance back to the road, the driver applies a rapid braking or steering maneuver $\boldsymbol{M}$, without closed-loop control. Variants of such a model, with T_R and $\boldsymbol{M}$ for example drawn from fixed probability distributions, have been



(a) *Sharp* et al. *[143]* (b) *MacAdam [101]* (c) *Gordon & Magnuski [59]* (d) *Salvucci & Gray [140]*

Figure 3.1: *Schematic illustrations of four models of steering from the literature. Specific implementation details can be found in Paper V.*

used not least in what-if resimulations of accidents [45, 150], also in more recent work, published after Paper IV was written [6, 83, 84, 126].

The delayed open-loop maneuver type of model clearly attempts to capture a specific near-crash type of behavior. Other researchers have instead adopted models or modeling paradigms from routine driving, applying them in near-crash simulation. Fig. 3.1 illustrates four examples of this approach, roughly representing four different types of model. The Sharp *et al.* [143] model in Fig. 3.1a is an example of a model inspired by **control theory**. Since the dawn of driver modeling, researchers with a good insight into the theory of automatic control of machines have likened the human driver to such controllers [71, 168]. Pedal or steering wheel control has thus been modeled as a function of a set of **control errors** to be minimized. In the Sharp *et al.* model, steering wheel angle δ is applied as:

$$\delta = K_\psi e_\psi + K_1 e_1 + K_\mathrm{p} \sum_{i=2}^{n} K_i e_i \qquad (3.1)$$

aiming to minimize the heading and lateral position deviations e_ψ and e_i from a **desired path**, as schematically illustrated in Fig. 3.1a. The $K_\cdot$ are **control gains**. In longitudinal **car-following**, typical control errors to minimize have been deviations from zero relative speed [50] or from a desired time headway [181]. A **neuromuscular delay** on the order of 0.2 s is often introduced between input and output.

As control theory has become more advanced, so have the driver models derived from it. In **optimal control theory**, the aim is to apply a control that is, in some sense, optimal. For example, the driver model by MacAdam [101], illustrated in Fig. 3.1b, applies the steering angle that minimizes an integral of predicted lateral deviation from the desired path. To achieve this prediction, the driver model relies on an **internal vehicle model**[1],

[1] In MacAdam's [101] model, this is a *linear one-track model*; see Paper V for a full formulation.

considered to operationalize the driver's acquired understanding of vehicle dynamics. An added practical benefit is that the same driver model may easily be reused together with many different simulated vehicles, accounting for behavioral adaptation to changing vehicle dynamics [103] by simply updating the internal vehicle model.

Other optimal control models have utilized more advanced, compound optimality criteria, for example to manage both longitudinal and lateral control at the same time, or to trade control accuracy against driver effort [21, 132]. The latter optimization trade-off is one way of accounting for the phenomenon of *satisficing* (introduced in Sect. 1.1), obvious especially in routine driving circumstances. The model by Gordon & Magnuski [59], illustrated in Fig. 3.1c and applied to collision avoidance in [23], also includes a basic internal vehicle model, but achieves satisficing more directly, by only applying steering corrections if the vehicle's current path violates a set of **boundary points**, representing edges of lanes or collision obstacles. The car-following model by Gipps [52] applies satisficing longitudinal control in a related fashion, and elaborated versions of this model have been applied in simulation of near-crash situations [62, 179].

All of the models presented above have taken a predominantly engineering-oriented perspective on driving, by emphasizing control and vehicle dynamics. Meanwhile, more psychology-oriented researchers have emphasized the question of what specific sources of perceptually available information, often referred to as **perceptual cues**, are used in driving control. For steering, it has been shown that limited visual information from one region close to the vehicle and one region further down the road is enough to reach the same performance as with a full visual field [89]. Consequently, the model by Salvucci & Gray [140], Fig. 3.1d, uses only the visual angles θ_n and θ_f to one **near point** and one **far point** for steering the vehicle towards a target lateral position:

$$\dot{\delta} = k_{\mathrm{nP}}\dot{\theta}_\mathrm{n} + k_\mathrm{f}\dot{\theta}_\mathrm{f} + k_{\mathrm{nI}}\theta_\mathrm{n} \tag{3.2}$$

Here, dots over quantities denote differentiation with respect to time. In other words, the Salvucci & Gray model starts rotating the steering wheel as soon as either the near point or the far point starts to move, or if the near point is not centered in front of the vehicle. It may be noted that Eq. (3.2) is rather similar in form to Eq. (3.1); the main difference lies in the choice of psychologically plausible perceptual cues as control errors, and the control of steering wheel rate $\dot{\delta}$ rather than steering wheel angle δ, inspired by [166]. Salvucci and colleagues [137, 139] have also integrated this steering control model into a more complete **cognitive architecture**, to allow simulation of a wider range of driver behavior, including execution of visually distracting secondary tasks [138].

While the review in Paper IV found many instances of near-crash behavior simulation, based on the abovementioned driver models and others, two clear research gaps were also noted. First, novel driver models had generally been proposed without comparing them to existing, competing models, leaving it unclear how similar or different the predicted behavior would actually be. Second, almost none of the proposed models had been validated on human behavior data from real or realistic near-crash situations. The main exception was the successful fitting of a Gipps-like longitudinal control model by Xin *et al.*, to a small set of actual recorded queue crashes [179]. In the cases where steering models like those shown in Fig. 3.1 had been tested against human steering, this was in the cone track type of scenarios described in Sect. 1.2, with questionable external validity.

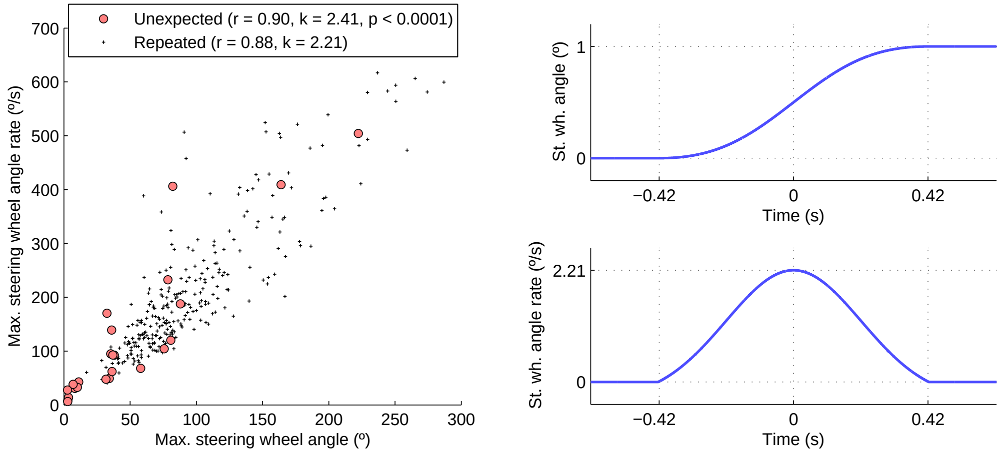
3.2 A comparison of steering models

In order to improve the understanding of how various near-crash behavior models relate to each other, the review in Paper IV provided limited simulation-based comparisons of a few braking and steering models, indicating that predicted behavior may sometimes be more similar than what can be readily deduced from the model equations. However, in order to select a steering model for the ESC use case, it was decided that a more thorough comparison was needed. This comparison, reported in full detail in Paper V, singled out the four models illustrated in Fig. 3.1 as promising alternative candidates for reproducing the behavior observed in the ESC simulator study. Initial experimentation indicated that some models were better at matching behavior in the early, collision-avoiding phase of the studied scenario, than behavior in the later stabilization-oriented phase, while for other models the opposite was true. Therefore, model parameter-fitting, by means of a **genetic algorithm (GA)** [65, 165] was carried out separately for these two phases. Since the aim was to study between-individual differences in steering behavior, the parameter-fitting was done at the level of the individual driver, using the data from the repeated scenario.

A few additional models were included. For the avoidance phase, an open-loop steering model was tested, in part because of its abovementioned prevalence in previous near-crash simulation, but further motivation was also found in the form of an observed correlation between maximum steering angle and maximum steering rate during avoidance; see Fig. 3.2a. This correlation, previously reported by Breuer [19], could be indicative of an open-loop, **ballistic** adjustment of steering wheel angle, where the final amplitude is determined before initiation (since adjustment speed predicts amplitude), with a duration that is independent of the amplitude (since the correlation is linear). Fig. 3.2b shows the specific steering adjustment profile adopted for the model in Paper V.

It had already been reported, in the author's licentiate thesis [106], that the Salvucci & Gray model was capable of good fits of the observed stabilization steering. Further analysis indicated that this ability was mainly due to the model's far point control, which had been shown, in the same thesis, to be equivalent to a type of **yaw rate nulling** control: $\dot{\delta} = -K\dot{\psi}$, where $\dot{\psi}$ is the vehicle's rate of yaw rotation. Therefore, such a model was tested directly.

Interestingly, the very simplest models were found to work rather well, with the performance of the more advanced models to some extent being dependent on an ability to exhibit the behavior of the simpler models. Fig. 3.3 illustrates how the open loop avoidance model was, overall, the most successful at reproducing the avoidance steering behavior, despite its relatively small number of free parameters. The best-fitting version of the open loop model reached an average **coefficient of determination** R^2, across all drivers and recordings, of 0.75 (meaning that it explained, on average, 75 % of the variance in the data [43]). This version of the model relied on internal models of own and lead vehicle movements to determine the amplitude of steering. However, a simpler version, applying avoidance amplitudes as a linear scaling of lead vehicle looming on the driver's retina, performed almost as well (average $R^2 = 0.71$). The second best model after the open loop model variants, the MacAdam model, was able to capture the observed pulse-like steering to some extent (average $R^2 = 0.49$). However, for example the Salvucci & Gray model, predicting $\dot{\delta}$ rather than δ, did not have this ability (average $R^2 = 0.20$).



(a) (b)

Figure 3.2: *(a) A correlation observed in the ESC simulator study, between amplitude and rate of collision avoidance steering. (b) The steering of the tested open loop avoidance model, here shown with the duration that would, theoretically, yield the slope k of the repeated-scenario correlation in (a). For full details, see Paper V.*

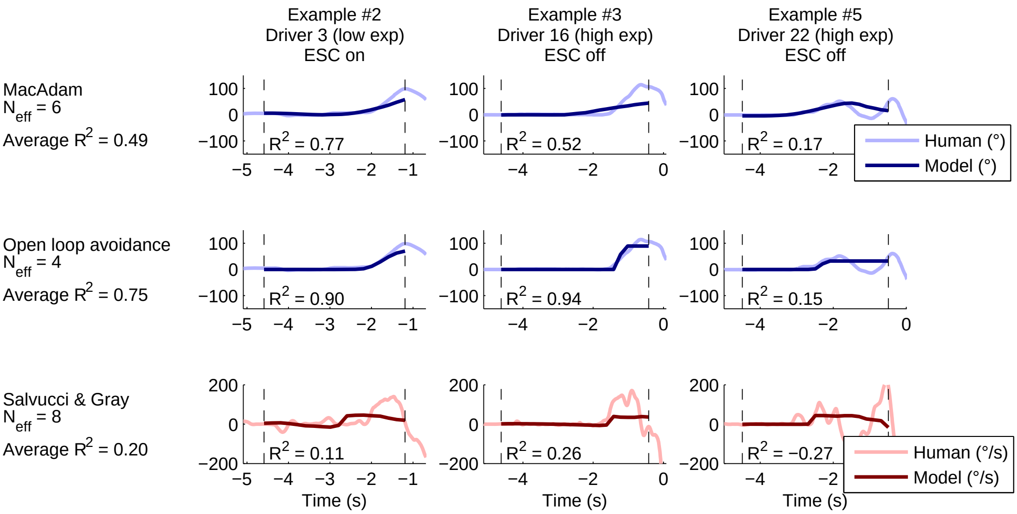


Figure 3.3: *Fits of human avoidance steering by three of the models tested in Paper V, in three example recordings, with reference numbers as in the original paper. N_{eff} is the number of model parameters influencing behavior in the avoidance phase. Average R^2 is measured across all drivers and scenario recordings. Note that the MacAdam and open loop avoidance models predict steering angle δ, whereas the Salvucci & Gray model predicts steering rate $\dot{\delta}$.*

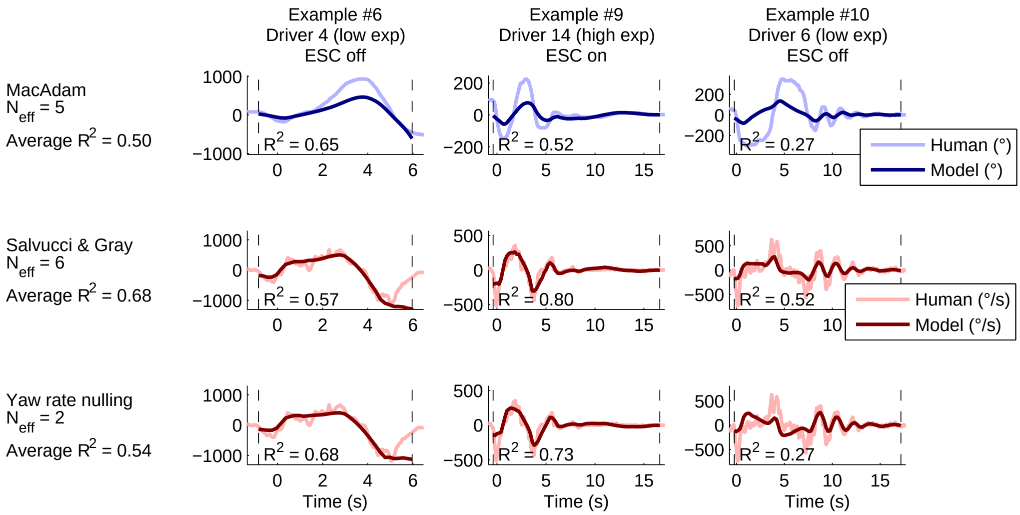


Figure 3.4: *Fits of human stabilization steering by three of the models tested in Paper V, in three example recordings, with reference numbers as in the original paper.* N_{eff} *is the number of model parameters influencing behavior in the stabilization phase. Average* R^2 *is measured across all drivers and scenario recordings. Note that the MacAdam model predicts steering angle* δ*, whereas the Salvucci & Gray and yaw rate nulling models predict steering rate* $\dot{\delta}$*.*

In stabilization steering, the most striking result was the good fit of the yaw rate nulling model. With only two free parameters (a neuromuscular delay T_{R} and the control gain K) it still reached an average R^2 of 0.54; see Fig. 3.4. Two types of cases with lower R^2 values for this model were recordings where (i) drivers seemingly gave up continued steering in the face of imminent control loss (Example #6 in the figure), and (ii) two novice drivers who possibly had a qualitatively different steering strategy (Example #10). Since, as mentioned above, yaw rate nulling is one independent component of the Salvucci & Gray model, this model should necessarily reach at least the same performance, and this was indeed the case. Furthermore, the additional model terms and parameters yielded an increase in average R^2, to 0.68. Interestingly, there was also a pattern of increasing fits for the yaw rate nulling model with increasing maximum yaw rates. This is compatible with a hypothesis of drivers steering as in the Salvucci & Gray model, because large yaw rates will cause the far point control component of such steering to dominate, making the yaw rate nulling model fit better.

The MacAdam model, on the other hand, did not have a benefit from having a larger number of parameters than the yaw rate nulling model[2], reaching an average R^2 of only 0.50. This limited performance, compared to the Salvucci & Gray model, is interesting with regards to the question of whether or not drivers make use of an internal vehicle

[2]For some further discussion on comparing models with different numbers of parameters, see Section 4.3 of Paper V.

model to follow an internally defined desired path. Arguably, the results in Paper V seem better in line with the notion of drivers employing what could be referred to as **sensorimotor heuristics**, with salient perceptual cues scaling rather directly into motor responses. It should be noted, however, that the internal vehicle model in the tested MacAdam model is linear, and although it can represent well what happens during routine driving, it does not include the effect of tires saturating when maneuvering starts to get too severe given the available road friction. Thus, strictly speaking, the results in Paper V indicate that the drivers in the ESC experiment at least did not seem to use this type of linear model, plausibly learnable from routine driving, when reacting to the skidding. In more recent work, MacAdam [102, 103] has shown how the use of nonlinear internal vehicle models yields a driver that can apply larger steering angles when the tires start saturating, and such more ample steering could indeed improve the fits in Fig. 3.4. So did the drivers in the experiment adapt their behavior in response to the low friction? One way of addressing this question is to return to the issue that was considered already in Chapter 2, but abandoned half-way, namely behavioral similarity between the unexpected and repeated scenarios.

3.3 Comparing steering behavior using models

In Paper V, between-scenario behavioral similarity was investigated by taking the models fitted to each driver's steering in the repeated scenario, and testing to what extent these models were able to predict the behavior of the same drivers in the unexpected scenario. Fig. 3.5 provides some details that did not fit in Paper V.

In contrast to the more blunt statistical methods in Paper II, the model-based analysis found indications of behavioral adaptation in collision avoidance steering, with larger steering amplitudes in repeated than unexpected avoidance; see Figs. 3.5a and b. Whereas observed steering in the repeated scenario tended to peak slightly above the model's predicted steering plateau (a pattern discernible also in Fig. 3.3), it tended to peak below the prediction in the unexpected scenario. This difference, illustrated in aggregate form in Fig. 3.5b, was statistically significant (median ratio ρ between observed and predicted steering maxima 1.32 and 0.81, for repeated and unexpected scenario; Wilcoxon rank sum $W = 622$; $n_1 = 141$; $n_2 = 16$; $p = 0.0002$). A natural interpretation is that the drivers learned that they had to apply more steering than usual to avoid the collision. One possible mechanism for this could be an update of an internal vehicle model.

However, as illustrated in Figs. 3.5c and d, there were no signs of a similar behavioral adaptation in the stabilization steering. The example from driver 21 bears possible traces of the higher steering wheel reversal rates noted in Paper II, but Fig. 3.5d demonstrates that, overall, the abovementioned correlation, between maximum yaw rate and the fit of the yaw rate nulling model, was more or less unchanged between the unexpected and repeated scenarios. Thus, if the drivers updated the friction estimate in an internal vehicle model, they must have done so during the unexpected scenario, precisely after collision avoidance and before stabilization. This is of course not impossible in principle, but it seems more plausible and parsimonious to assume that drivers instead employed sensorimotor heuristics, free from internal vehicle models, and that repeated exposure to

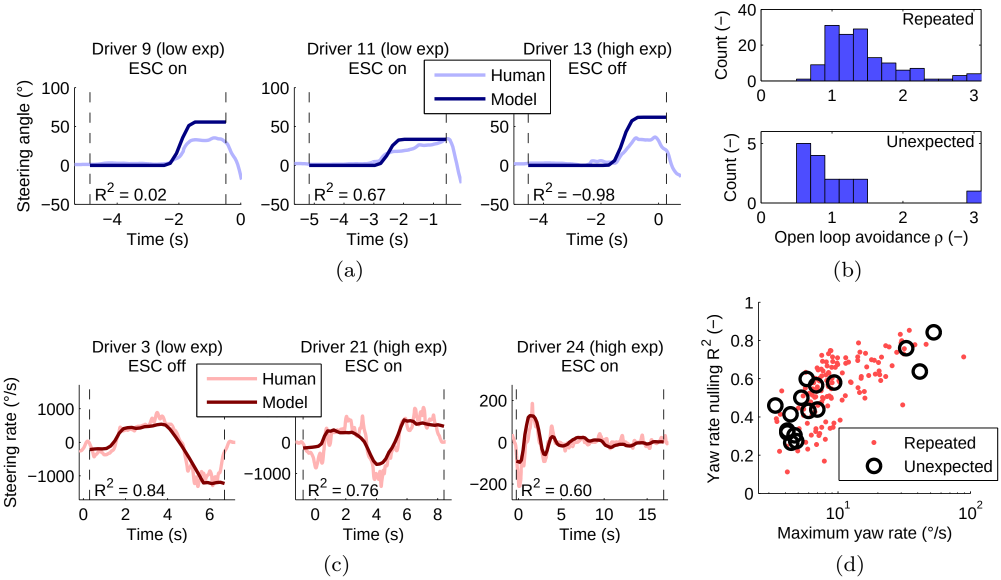


Figure 3.5: *Performance of models fitted to repeated scenario steering, when applied to unexpected steering. (a) Examples for the open loop avoidance model. (b) Ratio ρ between observed and predicted maximum avoidance steering. (c) Examples for the yaw rate nulling model. (d) Maximum observed yaw rate, and* R^2 *for the yaw rate nulling model, in individual scenario recordings.*

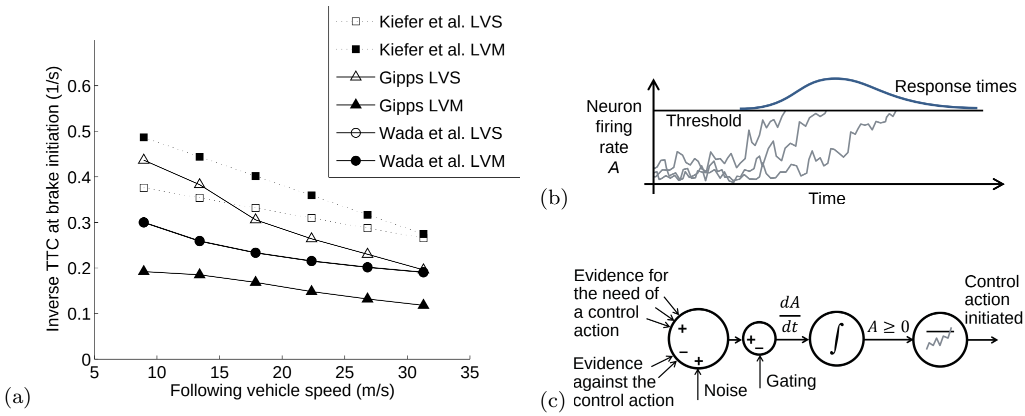


Figure 3.6: *(a) Brake onset timing in rear-end conflicts with a slower moving (LVM) or stationary (LVS) lead vehicle, according to three threshold-oriented accounts. The Gipps [52] and Wada* et al. *[163, 164] curves show predicted onset of normal braking whereas the Kiefer* et al. *[76, 77] curves indicate 75 % probability of* hard *braking. From Paper IV. (b) Schematic illustration of neuronal stochastic evidence accumulation. (c) The accumulator account of control action timing proposed in Paper VI.*

the fact that larger collision avoidance maneuvers than usual were needed caused them to re-scale their avoidance heuristic accordingly[3].

Besides fueling debates on how to model driver control, the evidence for between-scenario similarity in stabilization steering also allows a return to research question A of this thesis: *Does heavy truck ESC provide a safety benefit for normal drivers in realistic near-crash maneuvering?* In Chapter 2, it was demonstrated that ESC was helpful in the type of steering that drivers employed in the repeated scenario. Here, it has now been shown that this type of steering was indeed *the same* as in the unexpected scenario, motivating the answer that *yes*, ESC should provide safety benefits also when critical maneuvering is unexpected. The observed behavioral adaptation in collision avoidance steering is not in conflict with such a conclusion. Instead, it helps explain why skidding at levels prompting ESC intervention was so much more common in the repeated than in the unexpected scenario. As noted in Chapter 2, the repeated scenario elicited avoidance from lower TTC values, where more vigorous steering was needed, in turn creating more difficult vehicle stabilization challenges. Here, it has been shown that behavioral adaptation to the low friction invigorated the avoidance steering even further. Thus, one can conclude that the ESC experiment clearly led drivers into yaw instability much more frequently than in natural driving, but in the rare events of naturally occurring yaw instability, it is to be expected that drivers will respond to this instability in the same way as in the experiment, and that they will therefore be helped by ESC in the same way.

3.4 Response timing: kinematics and expectancy

One aspect of behavior that the model-fittings in Paper V did not address was *when* avoidance steering was initiated by the driver. The desired paths, open-loop pulses etc. were all defined relative to the actual, observed point of human steering initiation, effectively limiting the scope to just the question of *how* steering was carried out. This was deemed sufficient for the ESC use case, but in other contexts, such as in the AEBS use case, it may not be.

The review in Paper IV provided only limited guidance on this matter. Near-crash maneuver timing had basically only been considered in the delayed open-loop maneuver type of models, as fixed probability distributions of reaction times, typically averaging somewhere between 1 or 2 seconds. However, as touched upon in Chapter 1, simulator studies have indicated that reaction times after collision warnings *do* vary with situation kinematics, with longer reaction times in less critical scenarios [93, 100]. This dependency, somewhat reminiscent of satisficing behavior, seems crucial to a valid implementation of the AEBS use case, and hence the formulation of research question D of this thesis: *Is the timing of drivers' defensive maneuvers in rear-end conflicts dependent on the specific situation kinematics, and, if so, how can this dependence be modeled?*

In the context of routine driving, a number of kinematics-dependent models have been proposed for how satisficing drivers time their control actions. Here, the review in Paper IV provided an interesting result, shown in Fig. 3.6a: When comparing, in actual

[3] In addition, the desired path construct used in the MacAdam [101] model and many others can also be criticized in its own right; see Section 4.1.2 of Paper V.

simulation, two longitudinal control models that apply braking at clearly, but differently, defined thresholds, the obtained behavior was qualitatively similar to what had been reported from a test track study by Kiefer *et al.* [76, 77]: brake initiation at progressively lower inverse TTC for progressively higher values of the own vehicle's speed.

However, despite this local model convergence, the global conflict remains: In critical situations, late and unsafe responses are modeled with kinematics-independent probability distributions, whereas in non-critical driving, early and safe responses are modeled to occur at or before kinematic thresholds (e.g. looming thresholds; see also [41, 79, 148]). In Paper VI, a possible resolution to this conflict was proposed: *Timing of control is always probabilistic, but the distributions are affected by (among other things) both kinematics and expectancy.*

Specifically, it was noted in Paper VI that recent neurobiological models of action timing have highlighted a process of **evidence accumulation**, whereby evidence for an action's suitability is cumulatively integrated up to a fixed threshold for action execution; see Fig. 3.6b. With the rate of accumulation dependent on, for example, stimulus saliency, and affected by random variability in neuronal activity, this type of model has been able to account for response time distributions in a variety of laboratory tasks, and neurons have been found in animal brains that behave in the manner shown in Fig. 3.6b [55, 134–136, 145].

As illustrated schematically in Fig. 3.6c, it was suggested in Paper VI that timing of drivers' control actions could also be driven by accumulation, with a rate that is dependent on a wide range of perceptual cues. Some of these, like looming, brake light onsets, collision warnings, or upcoming intersections, could provide evidence for the need of defensive control action, whereas others, such as a lead vehicle turn indicator or a traffic light just shifting from red to green, could provide evidence against it. If so, control timing would be affected by situation kinematics, but a given kinematic situation could also trigger either a fast, safe response, if there was non-kinematic, anticipatory evidence for a need of braking (a high expectancy situation), or a slow, unsafe response if there was not (a low expectancy situation).

A simple mathematical realization of this idea was proposed in Paper VI, inspired by existing neurobiological models [134], as:

$$\frac{\mathrm{d}A(t)}{\mathrm{d}t} = C \cdot P(t) - M + \epsilon(t), \quad \text{with } A(t) \geq 0. \tag{3.3}$$

Here, $P(t)$ is some kinematics-dependent perceptual cue, C and M are model parameters, $\epsilon(t)$ is a noise term, and the control action occurs when $A(t) \geq A_{\mathrm{t}}$, another model parameter. M can be interpreted as the sum of all other evidence for and against the control action (smaller M for higher expectancy, and vice versa) together with a possible minimal gating level of input, needed to start the accumulation (see Fig. 3.6c).

As a first test, in Paper VI this model was applied to reports from the literature of response timing on the test track. It was shown that the model could account for previously unexplained effects [88] of kinematics on **detection thresholds** for looming, thus calling into question the notion of such tresholds being kinematics-independent, an assumption that, although not universal [16], is common in much driving safety research [88, 104, 122]. It was also shown in Paper VI that for scenarios with lead vehicle

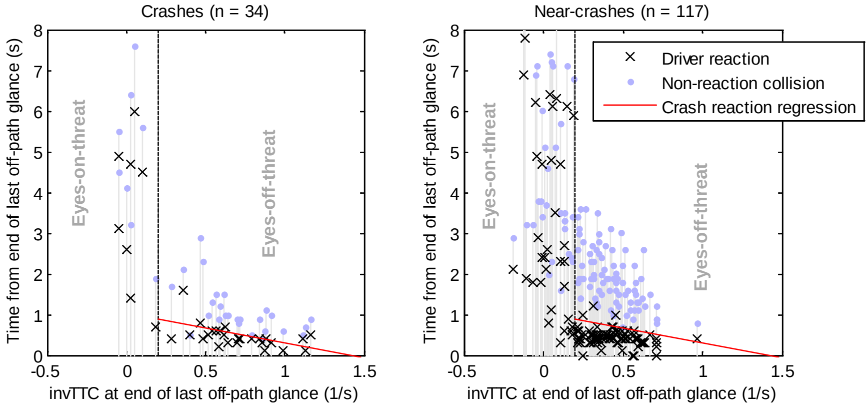


Figure 3.7: *Time from the end of the final glance off the forward path, until observed driver reaction (see Sect. 2.3) in the SHRP 2 crashes and near-crashes, as a function of inverse TTC. Also shown are estimated times to collision assuming no maneuvering from the driver, and a regression line for reaction timing in crashes with initial inverse TTC* > 0.2 *s*$^{-1}$ *(note that the exact same regression line, fitted to crashes, is shown in both panels). For full details, e.g. regarding inclusion and exclusion of events, see Paper III.*

deceleration in the above-mentioned experiment by Kiefer *et al.* [76, 77], the accumulator model provided a more fine-grained explanation of brake timing than the type of linearly decreasing functions proposed by Kiefer *et al.*, shown in Fig. 3.6a.

However, as has been repeatedly asserted in this thesis, it is not straightforward to relate behavior on test tracks to actual near-crash behavior. It is therefore of crucial importance that the response times in the SHRP 2 data set, with naturalistic rear-end crashes and near-crashes, were found (see Paper III) to follow exactly the type of pattern predicted by Eq. (3.3). Fig. 3.7 shows that in events where the driver glanced back to an already established conflict, with invTTC above 0.2 s^{-1} (mapping to the Category 1 and 2 crashes in Fig. 2.5, labeled in Fig. 3.7 as **eyes-off-threat**), times to reaction were short, generally below 1 s, and progressively shorter for increasing magnitudes of looming at the glance back to the road. Although weaker for near-crashes (Pearson $r = -0.25$) than for crashes ($r = -0.52$), this correlation was statistically significant for both event types, and can be understood as $A(t)$ integrating to threshold faster for higher $P(t)$.

In events where the last off-path glance ended *before* the onset of lead vehicle looming (Category 3 in Fig. 2.5, labeled in Fig. 3.7 as **eyes-on-threat**), the time from end of glance to reaction could be very long. Follow-up analyses showed that these reactions did not correlate in any apparent way with brake light onsets, but instead with looming reaching a certain magnitude; reactions started occurring at an invTTC around 0.2 s^{-1}, with the average reaction occurring around 0.5 s^{-1}. According to the Kiefer *et al.* curves in Fig. 3.6a, this is indicative of *hard* rather than *normal* braking, not surprising given that these events registered as at least near-crashes in the SHRP 2 analysis. In the terms of the accumulator model, such late reactions from drivers that are looking at the road ahead can be understood as M being higher than normal, due to low expectancy, delaying

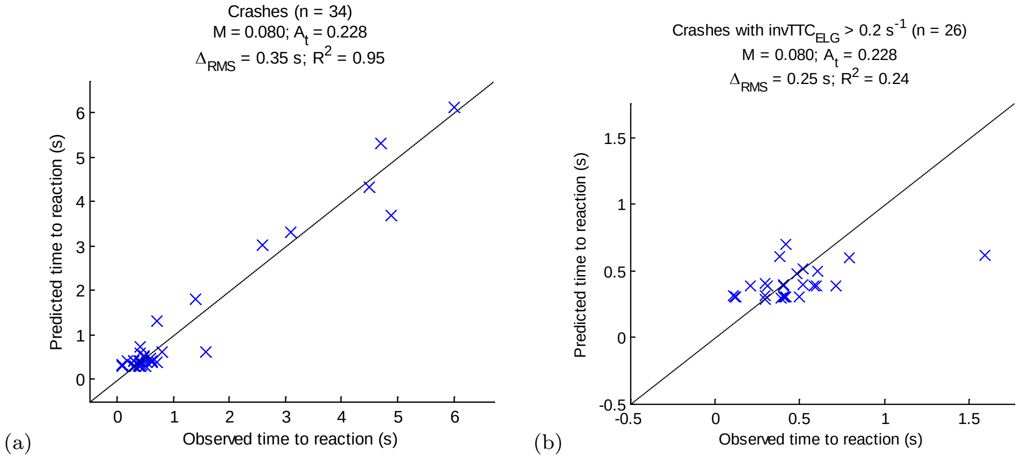


Figure 3.8: *(a) Fit of the accumulator model to observed time from end of last off-path glance until driver reaction, for the SHRP 2 crashes. (b) As (a), but zoomed in to show only the eyes-off-threat crashes, i.e. with inverse TTC above 0.2 s*$^{-1}$ *at the end of the last off-path glance. Both panels from Paper III.*

the start of looming evidence accumulation.

Paper III also attempted quantitative fits of Eq. (3.3) to the recorded events and driver reactions. As shown in Fig. 3.8a, it was possible to adjust (again using a GA) the parameters M and A_t such that the observed times of reaction were predicted with a **root mean square (RMS) error** of 0.35 s. It should be noted that, in itself, the high R^2 of 0.95 is not strong evidence for the accumulator model: Most of the variance in the response time data comes from variability in looming onset timing in the eyes-on-threat crashes, a variability that can be captured equally well by a threshold model (reaction a constant time delay after reaching an invTTC threshold). Instead, the strength of the accumulator model is that, in contrast to the threshold model, it can *also* account for the correlation between invTTC and reaction time in the eyes-off-threat crashes. The R^2 of 0.24 in Fig. 3.8b may not seem overly impressive, but corresponds closely to the linear correlation in Fig. 3.7, which had $R^2 = 0.27$; when similarly fitting the accumulator to just the eyes-off-threat crashes, it reached $R^2 = 0.28$. In other words, evidence accumulation can be confirmed as a potential mechanism behind the linear correlation, but does not provide any further predictive power beyond it. As discussed in Chapter 2, the remaining unexplained variability could be understood as due to variation in uncontrolled parameters, relating for example to expectancy (M, here fitted to a single, shared value for all events) or to underlying neuronal activity ($\epsilon(t)$, here set to zero).

Another issue to consider when fitting models to this type of naturalistic data, is the possibility of **selection bias**. For example, consider that in Paper III, reactions in crashes were shown to be, on average, 0.2 s slower than reactions in near-crashes. This is visible in Fig. 3.7, where the near-crash reactions can be seen to group below the regression line for crash reactions. This difference might be related to a number of factors that were more common in crashes than in near-crashes, such as young driver age, visual obstructions, rain etc. However, a delay of 0.2 s could just as well arise from natural variability in reaction times (due to an unfavorable $\epsilon(t)$), which could thus also be part of the reason why some events registered as crashes rather than near-crashes. Furthermore, natural variability in the opposite direction may have transformed some probable crashes into near-crashes, and near-crashes into non-events. Due to this type of phenomenon, rather than providing a complete and unbiased coverage of naturally occurring behavioral variability, a selection of critical events such as in SHRP 2 is likely to be biased towards those parts of the variability spectrum that lead to near-crashes and crashes, respectively.

Chapter 4
Simulation-based safety evaluation

The driver modeling work described in the previous chapter would have been much more difficult had it not been clear from the outset that the purpose of the models was their use in specific simulation-based evaluations of active safety. This helped delimit the range of behavioral phenomena to consider, and the need to sharpen this scoping process as much as possible inspired the concept of **use cases for driver-vehicle-environment (DVE) simulation**, as introduced in Chapter 1. In the context of active safety evaluation, such a use case should target one or more **pre-crash scenarios** [124], describing a flow of traffic events leading up to a potential crash, as well as a safety system designed to address this type of accident. These two components, the pre-crash scenario and the system addressing it, can be said to constitute an **active safety use case** [99], as exemplified in Fig. 1.1. However, a third component is also needed: the reason *why* one wishes to perform simulation, formulated in terms of a research question or an evaluation objective.

The first section below discusses how simulation-based evaluations of active safety can vary along a number of dimensions related to these three components, aiming to provide a structured understanding of previous work, and an overview of the possibilities. The remaining sections discuss simulation approaches for addressing the two specific use cases considered in this thesis. For the ESC use case, actual simulations and results are presented, previously only described in a project-internal report. For the AEBS use case, an initial sketch is provided of what a simulated evaluation could look like.

4.1 Types of simulation-based evaluation

The chart in Fig. 4.1 provides an illustration of the above-mentioned three components of simulation-based safety system evaluation, together with the most important ways in which these components may vary between evaluations.

With regards to the pre-crash scenario, one approach is to determine, e.g. from accident statistics, that a certain *type* of scenario deserves study, such as rear-end conflicts or fast double lane changes, and then manually define one or more *variations* of such a scenario [20, 82, 93, 119, 142, 144, 169]. Another possibility is to simulate large quantities of *routine driving*, including model mechanisms that can cause transitions into near-crash states [58, 180]. In recent years, however, it has become increasingly common to let *actual events* constitute the set of pre-crash scenarios to simulate. This approach allows a what-if type of evaluation, estimating how an active safety system could have affected specific situations from real life. Large numbers of such events can be obtained, albeit with much uncertainty in what really happened, from *crash reconstructions* [6, 29, 36, 44,

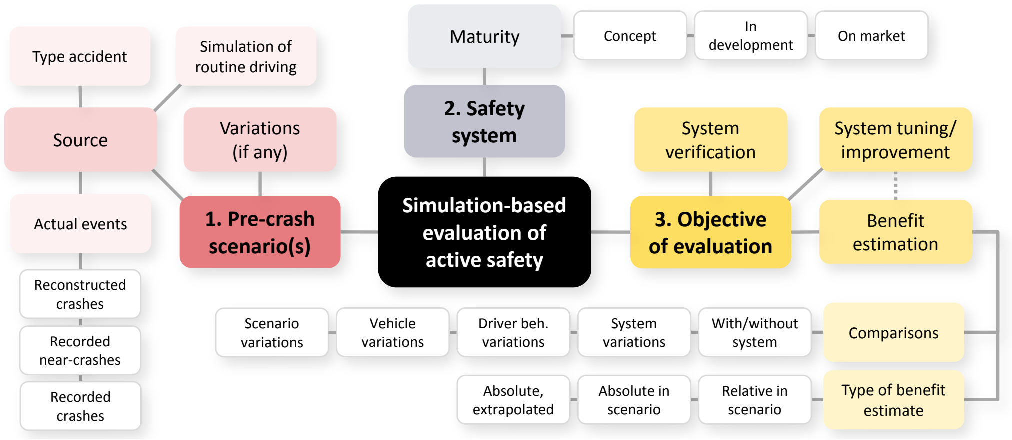


Figure 4.1: *Three components of simulation-based evaluation of automotive active safety, and different dimensions along which these components can vary in character.*

51, 80, 83, 84, 126, 149, 150]. The reconstruction uncertainty is reduced if the involved vehicles carry event data recorders [85], and in FOTs and naturalistic driving studies it is minimal. However, naturalistic studies have so far mainly recorded *near-crashes*, requiring additional assumptions if one is to predict reductions in crashes [45, 173, 174], thus instead introducing methodological uncertainty. The author is only aware of one single example of a what-if evaluation on actual *time-series recordings of crashes*, an FCW evaluation by McLaughlin *et al.* using the 100-car study data set [117]. Given the growing ubiquity of data loggers [35] one would expect this type of approach to become very important in the near future.

With regards to the *maturity* of the safety system being evaluated, simulations have been used to study systems along the entire development time line, from early *concept* stages [82, 119, 144], all the way to *on-market* systems [6, 45, 51, 58, 83, 150, 174].

By far, the most common *objective* of simulated evaluation has been to estimate the benefit of the studied safety system, and the most common *comparison* has been that of system present versus system absent. Some researchers have also been interested in the impact on system benefit of variations in pre-crash scenario [20, 82, 84, 142, 144], type of heavy vehicle combination [173, 174], or driver behavior [20, 51, 82]. In several cases, alternative versions or configurations of a system have been compared, occasionally with the explicit goal of *system tuning* [82, 93], an evaluation objective that is naturally related to benefit estimation. The end product in benefit estimation has either been *relative* figures within the studied pre-crash scenario (e.g. "20 % less crashes with the system than without it"), or *absolute* figures, typically extrapolated beyond the specific scenario to an entire crash population, such as prescribed in the Safety Impact Methodology (SIM) proposed in the NHTSA ACAT program [22, 48] that was mentioned in Chapter 1.

Finally, it may be noted that computer simulation can also be useful for *verifying* a system's compliance with technical specifications. Such evaluation typically does not require driver models, and is therefore not in focus here.

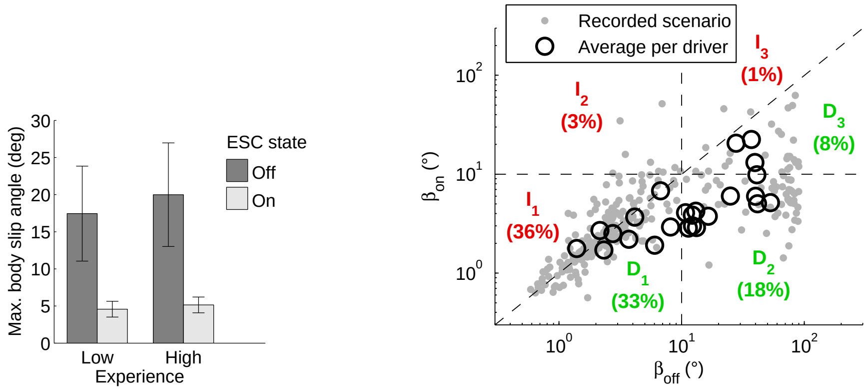
4.2 A simulation-based evaluation of ESC

The combination of statistical analysis (Chapter 2, Paper I) with model-fitting and behavior comparison (Chapter 3, Paper V) allowed the conclusion that, in general, heavy truck ESC should be beneficial in realistic situations with yaw instability. Research question B of this thesis, on the other hand, still remains open: *Is ESC equally useful for all drivers in realistic near-crash maneuvering?* A closer scrutiny of the recorded scenarios from the ESC simulator experiment showed that while ESC reduced average skidding and control loss at the group level, there were seven individuals out of the twenty-four (29 %) for which average skidding was actually slightly *higher* with ESC than without it. Here, however, one runs into a problem of too little data: Six measurements per driver and ESC state is not enough to prove individual-level system benefit for the driver who had the greatest *decrease* in skidding, let alone for the seven drivers with only very slight increases. In other words, rather than reflecting some interesting behavior phenomenon, the observed increases in skidding with ESC could just as well be random fluctuations due to natural behavioral variability (e.g. timing of avoidance initiation, speed of reaction to yaw instabilities, exact amplitudes of steering responses, etc.) just happening to turn up unfavorably in the measurements with ESC for these drivers.

As first discussed in Chapter 1, such limitations in experimental repeatability can be avoided by replacing the human subjects with driver models. Therefore, to address research question B, a kind of simulated replica of the ESC study was set up, using the same scenario and vehicle dynamics model as in the driving simulator, combined with the models that had been parameter-fitted to the twenty-four human drivers. To limit complexity, only the stabilization steering was model-based in these simulations, with the remainder of human control replayed, open-loop, from the actual experiment[1]. For each driver, all recorded scenarios were resimulated one by one, to begin with using the same ESC state as in the experiment. The truck was positioned in the center of the right lane, with the longitudinal speed and headway distance observed at lead vehicle brake onset in the specific scenario recording. Then, from this point of lead vehicle brake onset, the recorded human pedal and steering control were replayed in the simulation, up to the point of transition from avoidance to stabilization, as defined in Paper V. From this transition point onward, pedal control was still replayed from the recording, but steering was carried out by the Salvucci & Gray model, parameterized for the specific driver.

Thus far, the model should ideally do nothing more than simply reproduce what happened in the simulator study. As one indication of the extent to which this was the case, Fig. 4.2a shows the group-level effect of ESC on maximum body slip β in these simulations, to be compared with the same results from the simulator study, shown in Fig. 2.3b on page 14. From a qualitative perspective, it is clear that the model simulations

[1] Initial attempts were more ambitious, defining, in the terms of Sect. 4.1, the pre-crash scenario as a *type accident* rather than using the *recorded crashes and near-crashes* from the study. This required driver-specific models both for avoidance and stabilization steering, pedal control, as well as initial speed and moment of avoidance initiation. The obtained results were rather similar to what is presented here, but the multitude of models made interpretation, and comparison to the original simulator study, difficult. Another note to be made is that the approach adopted here disregards any dynamic interactions between pedal and steering behavior; this decision was based on the observation that the drivers in the simulator study generally maintained a roughly constant pedal position while steering.



(a) (b)

Figure 4.2: *(a) Effect of ESC at the level of experience groups, as observed in the replication of the ESC study with a driver model; to be compared with Fig. 2.3b. (b) Maximum body slip angle β observed in the model simulations without and with ESC, in each recorded scenario from the ESC study, as well as averages per driver. The percentages refer to the fraction of recorded scenarios falling within each sector of the plot.*

reproduced the general beneficial effect of ESC. With ESC on, also the absolute level of average skidding, around $\beta \approx 5°$, was approximately reproduced. However, without ESC the model drivers skidded much more in absolute numbers (average $\beta \approx 20°$) than the human drivers (average $\beta \approx 10°$), implying a larger relative effect of ESC in the model simulations than in the simulator study. One reason for this difference could be that for a given brake pedal input, the truck in the model simulation responded with slightly less deceleration than in the simulator (possibly due to minor modifications necessitated by a simulation software upgrade), such that stabilization in the model simulations was carried out at slightly higher speeds, rendering it more difficult.

However, the advantage of simulated evaluation is that one can do more than mere replication of an experiment with human drivers. Here, a type of what-if approach was adopted, by also simulating each recorded scenario a second time, with the opposite ESC state; i.e. ESC turned on if it had originally been off, and vice versa. In this way, for each specific initial condition, defined by the initial speed and recorded maneuvering up until the start of stabilization, it was possible to study the outcome both with and without the system. Since ESC affects lateral truck dynamics already during avoidance steering, and since the human drivers tended to shift from avoidance to stabilization at a roughly constant lateral truck position on the road, the shift to stabilization steering was set to occur, in these simulations, not at the same point in time as in the simulations with the original ESC state, but at the same lateral position.

Fig. 4.2b plots, for each recorded scenario thus twice resimulated, the maximum body slips β_{off} and β_{on} obtained without ESC versus with ESC. Any gray dot below the $y = x$ line (sectors D_1, D_2 and D_3) signifies a recorded scenario where the simulations indicated a decrease in skidding with ESC. Above this line (sectors I_1, I_2 and I_3), the simulations

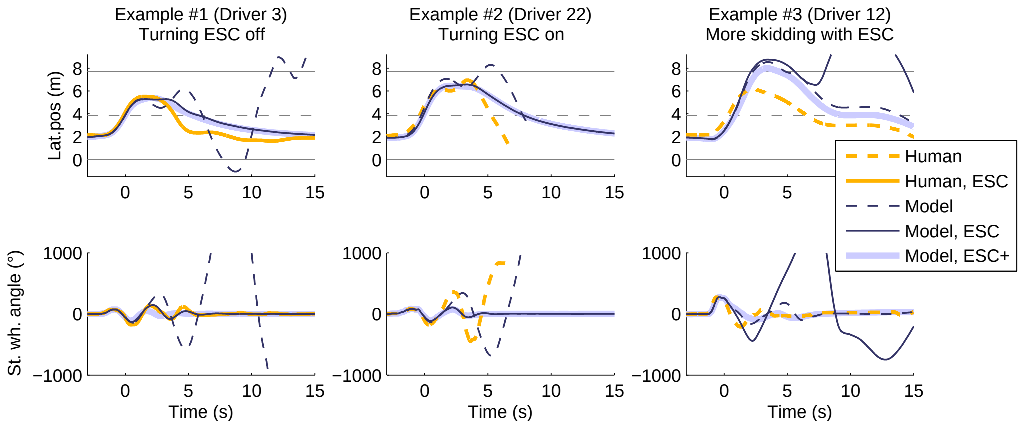


Figure 4.3: *Three recorded scenarios from the ESC simulator study, and their resimulation with a driver model for stabilization steering. Human driving is naturally only available for the ESC state of the specific recording, but model simulations are shown both with and without ESC, as well as with a modified version of the system (denoted ESC+).*

indicated an increase in skidding with ESC. Overall, there was a 60/40 ratio between ESC decreasing versus increasing skidding. However, it should be noted that the increases in skidding with ESC almost exclusively occurred at rather limited absolute levels, with both β_{off} and β_{on} below 10° (sector I_1). In the scenarios with severe skidding without ESC ($\beta_{\text{off}} > 10°$; the right half of the figure), ESC reduced skidding in 96 % of cases, and average $\beta_{\text{on}}/\beta_{\text{off}}$ was 0.27. In other words, the simulations predict that in situations where skidding is severe without ESC, system presence should, on average, reduce body slip by 73 %. Also, it can be noted that the per-driver averages are below or well below the $y = x$ line for twenty-one (88 %) of the drivers, and the remaining three are all only marginally above it and have average body slips below 10° both with and without ESC. In other words, based on Fig. 4.2b one possible answer to research question B of this thesis is that ESC is most useful to those drivers who have a hard time without it (average $\beta_{\text{off}} > 10°$), and that while there are individual scenarios where ESC is associated with increased rather than reduced skidding, there are no indications of any drivers having systematical problems with ESC-assisted steering.

Fig. 4.3 provides another perspective of what has been discussed above, in the form of three example recorded scenarios, and the simulated versions of the same scenarios, with various ESC settings. First, regarding the issue of how closely the models replicate closed-loop human control, one can compare the human behavior (the orange curves, solid or dashed depending on whether ESC was on or off in the specific recording) to the model behavior for the same ESC state (black curves; i.e. compare solid orange to solid black in Example #1 and dashed orange to dashed black in the other two). In Example #1, the human steering behavior is reproduced rather closely, however notably with considerable differences in lateral position, possibly due to the speed differences that were mentioned above as a potential cause of the higher absolute levels of skidding in the model simulations. Examples #2 and #3 suggest another possible cause for model instability, in terms of model steering being somewhat slower (lower steering rates) than the human steering[2]. In Example #2 the scenario outcome is nevertheless rather similar to the outcome in the simulator study, but in Example #3 the slower steering leads to a leftward lane exceedance that was not observed in the simulator.

Next, one can compare the results of model simulation with and without ESC (solid versus dashed black lines). Examples #1 and #2 show the most typical outcome, increased skidding when turning ESC off, and decreased skidding when turning it on, respectively. Example #3, however, is an illustration of the interesting worst-case sector I_2 of Fig. 4.2b, where a moderate skidding without the system becomes severe skidding with it. What seems to be happening here is that the ESC system responds to the leftward avoidance steering with interventions increasing leftward yaw rate and rotation, creating a larger initial instability than without the system. This initial instability develops into an oscillation that is too large for the driver and system to manage. Closer scrutiny of the scenarios in sector I_1 of Fig. 4.2b suggests that this same trade-off between collision avoidance efficiency and initial instability may be responsible also for these smaller increases in skidding with ESC. This type of vehicle behavior, sacrificing some stability in order to avoid a collision, may be desirable within reasonable bounds (e.g. sector I_1). However, one could argue that an ideal ESC system should somehow understand if avoidance steering is excessive, such as may have been the case in Example #3, and refrain from supporting it.

This general question, of how the ESC system should interpret the driver's actions, applies also during vehicle stabilization. Interestingly, the model-fitting results in Chapter 3 (Paper V) suggest some specific possibilities for system improvement in this area. Today's ESC systems typically assume that the driver behaves like the MacAdam model, applying steering wheel angles that would, under normal, high-friction conditions, produce the driver's desired vehicle movement [153, 183, 184]. However, the fact that the yaw rate nulling model fitted the human behavior during skidding better than the MacAdam model suggests that if the driver is applying fast rightward rotation to the steering wheel, a change of vehicle rotation towards the right is desired, regardless of whether the momentary steering wheel angle still happens to be toward the left. A patent application for this type of ESC system has been filed [109], and preliminary confirmation of its advantages has been obtained in a test track study [113]. Fig. 4.3 shows corresponding model simulations, here denoted ESC+, indicating comparable performance to a conventional ESC in some cases (Example #2), slight improvements in others (Example #1; note the smaller steering amplitudes), and in some cases drastic improvements (Example #3).

4.3 Sketch of an AEBS what-if evaluation

Returning, now, to the AEBS use case, consider Fig. 4.4, showing two recorded rear-end crashes from the SHRP 2 data set. How can this type of high-resolution time-series crash data best be used for active safety evaluation?

One possibility would be to adopt the methods for what-if evaluation that have

[2]This tendency is discernible also in Fig. 3.4, as the Salvucci & Gray model often not peaking quite as sharply as the human steering oscillations.

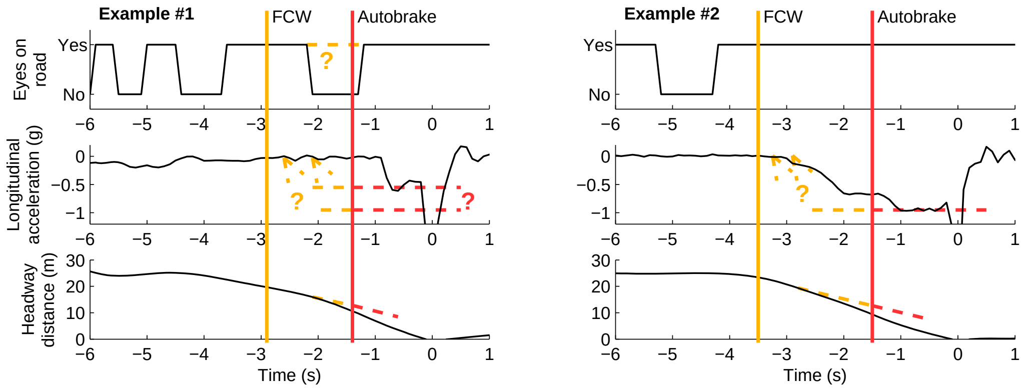


Figure 4.4: *Two example rear-end crashes from the SHRP 2 data set, with overlaid schematic illustrations of AEBS what-if simulation: The vertical lines show estimated times of activation for a hypothetical AEBS system, and the dashed lines suggest how driver behavior and scenario outcome could be estimated to change in consequence.*

previously been applied to test AEBS-like systems on *reconstructed* crashes [6, 51, 84, 150]. However, as is clear from Fig. 4.4, recorded crash data can offer very detailed information on driver behavior, such as where the drivers looked before the crash, and if, when, and how they responded with defensive control maneuvers. Denote this behavior information, described at some useful level of detail, with a vector $\boldsymbol{b}$. Since previous what-if evaluations have not had access to $\boldsymbol{b}$, typical existing methods would not use information of the kind shown in the top two panels of Fig. 4.4, replacing it instead with probability distributions $P(\boldsymbol{b})$ for glance behavior, reaction times, maneuver amplitudes etc. From the recorded crash, it is typically only the observed crash kinematics $\boldsymbol{K}$, before any driver reaction, that is used as input to the benefits estimation method. Thus, rather than considering an observed crash as an actual crash, one considers it a *potential* crash, with uncertainty arising from $P(\boldsymbol{b})$. System effectiveness $E(\boldsymbol{K})$ is estimated, for example, as [6]:

$$E(\boldsymbol{K}) = 1 - \frac{\text{Prob}\left[\text{Crash}|\boldsymbol{K}, \text{With system}, P(\boldsymbol{b}|\boldsymbol{K}, \text{With system})\right]}{\text{Prob}\left[\text{Crash}|\boldsymbol{K}, \text{Without system}, P(\boldsymbol{b}|\boldsymbol{K}, \text{Without system})\right]} \tag{4.1}$$

Here, for example $\text{Prob}\left[\text{Crash}|\boldsymbol{K}, \text{With system}, P(\boldsymbol{b}|\boldsymbol{K}, \text{With system})\right]$ should be interpreted as the probability of crash, given a scenario with kinematics $\boldsymbol{K}$ where the safety system is present, calculated by summing over the probability distribution for driver behaviors in this scenario. Note that $E(\boldsymbol{K}) = 0$ if crash probability is the same with and without the system, and $E(\boldsymbol{K}) = 1$ if crash probability with the system is zero. Also note the dependence of $P(\boldsymbol{b})$ on $\boldsymbol{K}$; this is not a part of existing methods, but is included here because of the insights on kinematics-dependence of reaction timing presented in Chapter 3 (Paper III). Also other kinematics-dependencies could be argued for, such as driver glance behavior being affected by looming [155].

Besides the requirement to accurately account for many aspects of driver behavior, including dependencies on kinematics, a possible general limitation of the approach expressed in Eq. (4.1) is that it uses the highly detailed recorded kinematic information

$\boldsymbol{K}$ but completely disregards many driver-related factors $\boldsymbol{D}$, such as driver expectancies, driver drowsiness, visibility conditions, and so on, which may in practice have had an impact on both $\boldsymbol{K}$ and $\boldsymbol{b}$. For example, if a certain class of $\boldsymbol{K}$ would be more probable to occur for drowsy drivers, using a general, non-drowsiness-specific distribution of driver behavior $P(\boldsymbol{b})$ when simulating such events could lead to incorrect benefit estimates. Another, related, objection is that Eq. (4.1) does not really address research question C of this thesis: *For a given recorded rear-end crash, what would have happened if AEBS had been present?* Instead, as stated above it relies on the idea of trying to estimate a *crash probability* inherent in a traffic situation with given kinematics, regardless of driver-related factors, and tries to measure how this probability changes with AEBS.

A possible alternative approach, more along the lines of research question C, can be devised by acknowledging that even if the observed driver behavior in the recorded crash, denoted $\boldsymbol{b}_{\mathbf{C}}$ for clarity, does not provide a complete understanding of the factors $\boldsymbol{D}$, it provides at least some indications. For example, if $\boldsymbol{b}_{\mathbf{C}}$ shows a later driver response than what is observed on average for the kinematics $\boldsymbol{K}$, something which could be due to drowsiness, low expectancy, limited visibility, and so on, then one could argue that the driver response with the system would probably also have occurred later than the average response under those conditions[3]. In such an approach, one could treat the observed crash, defined by both $\boldsymbol{K}$ and $\boldsymbol{b}_{\mathbf{C}}$, as an actual crash (with probability one), and replace Eq. (4.1) with:

$$E(\boldsymbol{K}, \boldsymbol{b}_{\mathbf{C}}) = 1 - \text{Prob}\left[\text{Crash}|\boldsymbol{K}, \text{With system}, P(\boldsymbol{b}|\boldsymbol{K}, \text{With system}, \boldsymbol{b}_{\mathbf{C}})\right] \tag{4.2}$$

The challenge here is to formulate an expression for $P(\boldsymbol{b}|\boldsymbol{K}, \text{With system}, \boldsymbol{b}_{\mathbf{C}})$, an estimate of what the same crash-involved driver, i.e. the one who originally responded with $\boldsymbol{b}_{\mathbf{C}}$, would have done in the same situation if the system had been present. For the AEBS use case, such modeling work is underway, supported by analysis of SHRP 2 and similar data sets, data from a simulator study on how situation kinematics, warnings, and interventions interact to influence driver response, and a modeling framework to be presented in the next chapter.

Overlaid on the crash events in Fig. 4.4 are schematic illustrations of the uncertainties that should be captured and narrowed down as much as is plausible by this driver model. The first question concerns eye movement behavior; here previously mentioned work [93, 100, 167] suggests that the model should respond to collision warnings by reorienting gaze towards the road ahead, and possibly, as in the left panel of Fig. 4.4, omitting any further off-road glances. Next, timing of maneuver onset, most often braking onset [94, 170], is estimated from this new glance pattern combined with a driver and situation-specific sensitivity to looming that is, as hinted at above, estimated from the observed behavior $\boldsymbol{b}_{\boldsymbol{C}}$ in the actual crash. In what concerns maneuver speeds and amplitudes, Fig. 4.4 shows clearly that there are large differences between events also in this respect, and the current strategy is to model also these in an event-specific way.

Overall, the idea is for the model to have what could be called the **resimulation property**: When one resimulates the observed crash event with no or minor modifications, something very close to the actual observed behavior should be predicted. Mathematically,

[3]Georgi *et al.* [51] seem to have done something along these lines, by estimating timing and type of driver response from the accident reconstruction, but they do not describe their method in detail.

$P(\boldsymbol{b}|\boldsymbol{K}, \text{Without system}, \boldsymbol{b}_\mathbf{C})$ should be close to 1 for $\boldsymbol{b} \approx \boldsymbol{b}_\mathbf{C}$, and close to 0 for other $\boldsymbol{b}$. Since this clearly implies parameter-fitting of the model to each individual event, an added requirement on the model and method is that the risk of overfitting should be managed. One possibility, here, is to keep the model maximally simple, another could be to consider ranges of possible model parameters as part of the uncertainty in $P(\boldsymbol{b})$.

Concerning steering avoidance, the current idea is to make use of the insights from Chapter 3 (Paper V), that its execution can be modeled as an open-loop pulse, and from Chapter 2 (Paper I), that its occurrence can be modeled as a distribution of an onset timing that may or may not occur before collision. Here, there is less empirical data in general, but very high fidelity of the steering model may anyway not be warranted, since, for most crashes, there will be large uncertainties as to whether steering avoidance would really have been a feasible option given the surrounding traffic and infrastructure.

In cases where the model driver's braking or steering response is not sufficient, automatic braking will ensue, and from this point on there is much less uncertainty, since the system's behavior will typically be well understood. A specific issue to deal with, however, is observable in the middle left panel of Fig. 4.4, where the driver's deceleration stays at rather moderate levels (before the crash impulse at time zero). This limited deceleration could be due to a staircase-like behavior from the driver, similar to what is seen in the rightmost example of the same figure, but just as well to low road friction or bad brakes. Uncertainty of this kind should be reduced as much as possible by investigating the events in question in more detail (using videos, annotator narratives, etc.), since there is a clear impact on what maximum decelerations to allow in the what-if simulation.

Chapter 5
Frameworks for driver modeling

In the research behind this thesis, attempts at *the* universal driver model, applicable in any and all traffic scenario, have been deliberately avoided. Instead, to ensure feasibility, modeling has been tightly constrained, and this has been a successful approach, in the sense that answers have now been provided for all research questions identified in Chapter 1, for the ESC and AEBS use cases. However, it should also be noted that the AEBS use case has still not been addressed in its entirety, and many important road accident types and safety systems remain that have not at all been approached here. From an applied point of view, this can raise concerns of cost-efficiency; will each new system evaluation require another PhD project to develop its driver models? If so, simulation-based evaluation will be considerably more expensive than the best-case scenario suggested in Table 1.1.

One means of improving future model development cost-efficiency is to use the insights gained from the use case-specific modeling for identifying principles and mechanisms that might be more general, and which could thus be reusable when addressing new use cases. In other words, rather than defining a universal driver model, one can define a *framework* for modeling.

The first section below outlines such a framework, originally presented in Paper VI, aiming specifically at unifying typical models of routine driving control with typical models of more critical maneuvering. The other section of this chapter provides a look, slightly more detailed than in Paper VI, at how the proposed modeling framework can be put in contact with the vehicle dynamics aspects of driver control behavior.

5.1 From routine driving to near-crash driving

As was mentioned in Chapter 3 (Paper IV), quantitative driver models aimed specifically at near-crash behavior are rather scarce. However, comparing those accounts that do exist, of which the delayed open-loop maneuver model (see p. 19) is the most typical example, to the considerably more numerous models of normal, non-critical driving, some glaring differences are evident: Routine driving has repeatedly been characterized as continuous, closed-loop, short-latency control, well-adjusted to vehicle dynamics, sometimes even to the point of optimal control. In contrast, near-crash behavior has been modeled as discrete open-loop maneuvers, occurring after delays that are very long given the severity of the situation, and with amplitudes that are basically random, possibly based on empirical reports that near-crashing drivers will often underreact [3, 81, 90] or overreact [105, 175]. When modelers have considered thresholds or similar constructs that postpone driver control, the typical approach in routine driving models has been to introduce effort-

Table 5.1: Typical characteristics of routine and near-crash driver behavior models.

Routine driving	**Near-crash driving**
Continuous closed-loop control	Discrete open-loop maneuvers
Short neuromuscular delays ($\approx$ 0.2 s)	Long reaction times ($\approx$ 1-2 s)
Well-adjusted or optimal control	Under- and overreactions
Satisficing thresholds	Detection thresholds

limiting, satisficing constraints [52, 59, 132], whereas in near-crash control, minimum detection thresholds for e.g. looming have been given more attention [104, 122]. Table 5.1 summarizes these differences.

The modeling framework in Paper VI is an attempt at reconciling these two seemingly incompatible model classes, by proposing a set of four assumptions on underlying mechanisms, and arguing that these assumptions can account for both columns in Table 5.1.

The first assumption is that, at its most basic level, all control is open-loop, in the sense that it is constructed from a series of **intermittent** adjustments of a ballistic nature; i.e. adjustments occur sporadically, and the shape of each adjustment is determined at its onset. This idea was inspired by the neuroscientific finding that at the spinal level, all body movement seems to be constructed from small bursts of muscle activity [53, 72]. Indeed, if one looks for intermittency in driver control behavior, one finds it: Fig. 5.1 shows examples of naturalistic driving control, where the rates of change of pedals and steering wheel are mostly zero, but with upward and downward spikes of activity. In collaboration with Benderius [10], quantitative evidence has also been found that steering, in a wide variety of scenarios, is composed of such burst-like adjustments, with amplitude-independent durations of about 0.4 s. In his thesis, Benderius [9] has elaborated further on this topic, and has suggested a steering model that shares several features with the framework being presented here.

With regards to the issue of routine versus near-crash control, the intermittent open-loop control assumption helps resolve the first contradiction in Table 5.1: Most often in driving, adjustments are small and frequent, such that the overall behavior can be described rather successfully as continuous closed-loop control, whereas in critical situations, with need of severe maneuvering, the underlying open-loop nature of control becomes more evident.

Also other authors have considered intermittency in driving control [13, 57, 59, 139] or in human control more in general [49]. One thing that sets the framework in Paper VI apart from this existing work is the second framework assumption, suggesting that the timing of individual control adjustments is driven by the type of evidence accumulation process that was described in Chapter 3. In such a process, graded perceptual cues, like visual looming or movement of sight points, could be combined with other evidence regarding the need for control adjustments. It was discussed already in Chapter 3 how such a mechanism could explain short-latency reactions in routine conditions, and long-latency reactions in atypical, unexpected situations, thus accounting for the second contradiction in Table 5.1. Besides low expectancy, one could also consider for example drowsiness

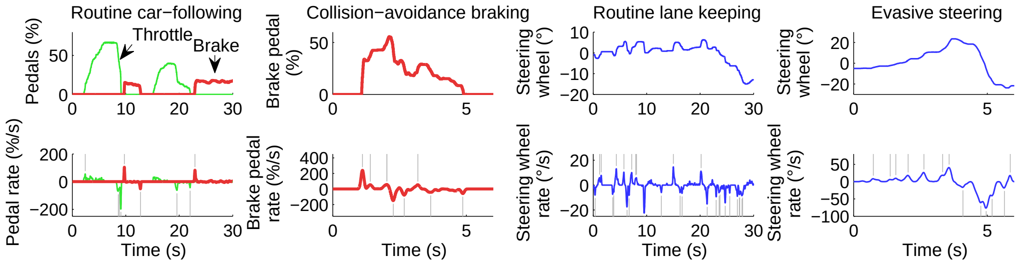


Figure 5.1: *Driver pedal control (left half of the figure) and steering control (right half) in four different instances of naturalistic truck driving, from a Volvo Trucks data set. The upper panels show pedal and steering wheel positions, and the lower panels show the corresponding time derivatives, where the intermittent nature of control becomes visible, highlighted further with vertical gray lines at each burst of activity. From Paper VI.*

within this framework; it has been shown that drowsiness-related increases in reaction times can be understood as slower and more noisy evidence accumulation [136].

Furthermore, it was also discussed in Chapter 3 how the results in Paper VI cast clear doubts on the idea of canonical, situation-independent thresholds for stimulus detection, and the same applies to satisficing thresholds: Within a specific context or scenario, thresholds for detection or satisficing control action might be empirically identifiable, but if evidence accumulation is involved, a different scenario, e.g. with different kinematics, will lead to observation of different thresholds. In other words, the evidence accumulation assumption implies that the types of threshold mentioned in the fourth row of Table 5.1 might not be very useful in contexts where more than one constrained scenario is being considered.

What about the size of individual control adjustments? Since routine driving seems well-adapted to the driving situation and vehicle dynamics, steering and pedal amplitudes can hardly be random. The third framework assumption is that control adjustments are scaled to resolve the conflict that triggered them. Qualitatively speaking, this means that more severe conflicts will generate larger control adjustments. Fig. 5.2a shows two simulations of a driver braking control model in which the pedal adjustments have an amplitude B as follows:

$$B = k\frac{1}{\tau} \equiv k\frac{\dot{\theta}}{\theta}, \tag{5.1}$$

that is, a linear scaling of the amount of visual looming at the time of adjustment initiation. In these simulations, a lead vehicle starts decelerating at time $t = 2$ s, and after an initial accumulation of looming evidence (which is faster in the more critical scenario because of the higher looming levels), there is a first brake pedal adjustment. Here, for a k that yields a well-adapted braking response in the moderate deceleration scenario, it is clear that the linear heuristic results in an initial underreaction in the more critical scenario.

What is suggested here is that with experience, drivers could come to learn heuristics that allow near-optimal performance in routine driving, but which become suboptimal outside this constrained operating regime. Such a phenomenon could be one of several causes for the third apparent contradiction in Table 5.1. As also mentioned in Paper VI,

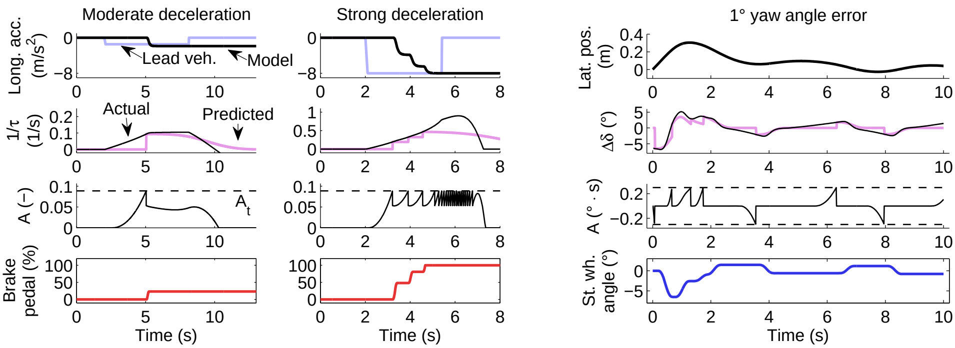


Figure 5.2: *Example simulations based on the driver modeling framework outlined in Paper VI. (a) Braking in two scenarios with risk of rear-end collision, differing only in the magnitude of lead vehicle deceleration. From Paper VI. (b) Lane-keeping steering in response to an initial yaw angle error.*

another potentially relevant phenomenon is **signal-dependent motor noise** [47]; random variability in motor performance that scales with movement amplitudes, such that larger steering or pedal adjustments should be more likely to end up far, in absolute terms, from what was intended by the driver.

In the hard-braking scenario of Fig. 5.2a, the initial underreaction is compensated for with increased brake pedal pressure. The fourth and final assumption of the proposed modeling framework is motivated by the neuroscientific hypothesis that the brain learns to predict the sensory consequences of motor actions, and uses these predictions to achieve stable sensorimotor control: For each motor command sent to the spine and muscles, the brain is thought to generate a **corollary discharge** signal communicating expected sensory input [24, 73], possibly by routing an **efference copy** of the motor command via brain structures, for example the cerebellum, where **forward models** of the environment have been learned [47].

Here, it is suggested that such predictions could be used to inhibit additional control adjustments until the vehicle and traffic situation has had time to respond to previous adjustments. In the example simulations shown in Fig. 5.2a, a brake increase is predicted by the driver model to cause $1/\tau$ to fall back to zero within a specific time, and in the less critical scenario this prediction is good enough to prevent any further brake pedal movement. In the more critical scenario, however, the same prediction is repeatedly violated, leading to a staircase pattern of brake pressure increases. Such a pattern has been previously reported for unexpected critical braking [133], and the reader may remember it also from the rightmost SHRP 2 example in Fig. 4.4 (p. 39).

5.2 From sensorimotor heuristics to vehicle dynamics

Thus far, of the four suggested framework assumptions, initial experimental support has been provided for the first two, regarding control intermittency (in the paper with Benderius [10]) and evidence accumulation (Papers III and VI). Awaiting further empirical investigations, at least assumption three can also be addressed from another, more theoretical angle: Are the assumed sensorimotor heuristics, well-adapted to vehicle dynamics without an explicit internal vehicle model, possible even in theory?

This question was given some initial attention in the author's licentiate thesis [106, pp. 29–32]. Specifically, in relation to the steering heuristics suggested by the Salvucci & Gray [140] model, it was shown that when driving in the middle of a straight road with the vehicle pointing straight ahead, but with a small error in yaw rate $\dot{\psi}_{\mathrm{err}}$, a driver will perceive a far point rotation $\dot{\theta}_{\mathrm{f}} \approx -\dot{\psi}_{\mathrm{err}}$. Therefore, since the vehicle response to steering angle δ, and thus to steering changes $\Delta\delta$, is linear under normal circumstances:

$$\dot{\psi} = S(v_x)\delta \quad \Rightarrow \quad \Delta\dot{\psi} = S(v_x)\Delta\delta, \tag{5.2}$$

an appropriate steering wheel adjustment for remedying the yaw rate error is optically available to the driver as:

$$\Delta\delta = \frac{1}{S(v_x)}\Delta\dot{\psi} = \frac{1}{S(v_x)}(-\dot{\psi}_{\mathrm{err}}) \approx \frac{1}{S(v_x)}\dot{\theta}_{\mathrm{f}}, \tag{5.3}$$

where $S(v_x)$ is the speed-dependent steady-state yaw rate response of the vehicle (see e.g. [70]). This result indicates that the far point term of the Salvucci & Gray model can be part of steering heuristics that are well-adapted to vehicle dynamics[1].

In a similar fashion, it can be shown that for the general case of small arbitrary errors in lateral position, yaw angle and yaw rate, and arbitrary constant road curvature, the entire Salvucci & Gray equation can be obtained, for example on the following form:

$$\Delta\delta \approx \frac{1}{S(v_x)}\left[\frac{\tau_{\mathrm{n}}}{T^2}\theta_{\mathrm{n}} + \frac{\tau_{\mathrm{n}}}{T}\left(\frac{3}{2} - \frac{\tau_{\mathrm{n}}}{T}\right)\dot{\theta}_{\mathrm{n}} + \dot{\theta}_{\mathrm{f}}\right]. \tag{5.4}$$

Note that this is exactly the same control law as in Eq. (3.2), but with the three control gains k_{nP}, k_{f}, and k_{nI} replaced by the single, more easily interpreted parameter T, specifying the time within which the driver aims to resolve steering errors. τ_{n} is the near-point preview time. A presentation of the assumptions and derivations leading up to Eq. (5.4) is beyond the scope here, but will be submitted for publication elsewhere [107].

As a further illustration of the modeling framework proposed in Paper VI, Fig. 5.2b shows an example simulation where Eq. (5.4) is used to model steering response to a small initial error in yaw angle. Again, full details will not be provided here, but it can be noted that (i) the accumulator now has two thresholds, one for each direction of steering adjustment, and (ii) the $\Delta\delta$ quantity has the same role, here, as $1/\tau$ in the braking model, making the expression in Eq. (5.4) serve as a form of compound perceptual cue[2]. In terms

[1] Specifically, Eq. (5.3) suggests that a driver who learns how to scale a steering wheel adjustment to a rotating far point is in fact learning the inverse of the vehicle's steady state yaw rate response.

[2] Alternatively, one could consider each of θ_{n}, $\dot{\theta}_{\mathrm{n}}$ and $\dot{\theta}_{\mathrm{f}}$ as separate cues, each with an accumulator of its own.

of model behavior, it can be noted that the first rightward (negative) steering adjustment is followed by a quick succession of three leftward adjustments that, together, give the steering signal more of a closed-loop aspect than an open-loop one. After this initial phase of lateral stabilization, satisficing lane-keeping ensues with small adjustments about every two seconds, qualitatively similar to what can be seen during the first 20 seconds of the routine lane-keeping example in Fig. 5.1. (From about 20 s, that example shows an entry into a curve.)

Of course, the type of mathematical analysis leading up to Eqs. (5.3) and (5.4) by no means proves that drivers really use the steering heuristics proposed by Salvucci & Gray[3]. However, the analyses do show that (and how) these heuristics are capable of resolving small control errors during routine lane-keeping, in a manner that is well-adapted from a vehicle dynamics perspective. The other side of the same argument is that if the control errors grow larger, the same heuristics will no longer be well-adapted. For example, as discussed in Chapter 3, when yaw rate errors grow unusually large during skidding, the far point component of Eq. (5.4) will come to dominate, leading to yaw rate nulling steering, overcompensation, and potential control loss. The specific reason why this strategy is no longer well-adapted is that Eq. (5.2) does not hold during skidding; with the tires partially or fully saturated, increased steering no longer produces increased yaw rates in the same predictable way as under routine circumstances.

Besides providing insight into which control heuristics are well-adapted, and under what circumstances, the connection between sensorimotor heuristics and vehicle dynamics also has applied value. Without this connection, a given driver model relying on sensorimotor heuristics would have to be re-parameterized for each new vehicle type and model, whereas a formulation such as that in Eq. (5.4) provides direct (and empirically testable) predictions regarding how a change in vehicle dynamics should affect driver behavior. As the reader may recall from Chapter 3, also driver models based on internal vehicle models are capable of such predictions. However, since it has been argued in this thesis that such driver models are not suitable for simulating non-routine, critical situations, the type of approach outlined here clearly has a purpose to serve.

[3]For example, near-region control could possibly be better understood as staying away from lane boundaries, in a similar vein to what has been suggested by Gordon and colleagues [57, 59], rather than optimizing towards a certain lane position.

Chapter 6
Conclusions and future work

In summary, four main research questions have been pursued, in the context of simulation-based evaluation of ESC and AEBS systems. Below, all four questions will be revisited, before concluding with some considerations on simulation-based safety evaluation from a broader perspective, as well as on the secondary research aim of this thesis: more general frameworks for driver modeling.

6.1 The ESC and AEBS use cases

Research question A: Does heavy truck ESC provide a safety benefit for normal drivers in realistic near-crash maneuvering?

It has been shown, here, that (i) the heavy truck ESC system provided a statistically significant benefit in repeated exposure to low-friction collision-avoidance in a driving simulator, and (ii) unexpected exposure to the same scenario, which is as close as one gets to full realism in the simulator, elicited stabilization steering behavior that could be successfully predicted by driver models fitted to the repeated-scenario steering. Finding (ii) implies that stabilization behavior was similar between unexpected and repeated exposure, and therefore (i) and (ii) together motivate the conclusion that, *yes*, the ESC system can be expected to provide a benefit in realistic near-crash maneuvering. Safety benefits of ESC in realistic situations have been demonstrated previously for passenger cars [67, 130], but this is the first such demonstration for heavy trucks.

Two main limitations, which could be addressed in future work, were the use of just a single ESC-targeted scenario, and the fact that the study was carried out in a driving simulator, leaving it unclear to what extent observed behaviors and system effects generalize to real vehicles and real traffic. The second limitation has to some extent been addressed in a follow-up study on a test track [113].

In the process of answering research question A, some novel results on driver steering behavior were obtained as well: Collision-avoidance steering was found to be best characterized as an open-loop pulse of steering wheel adjustment, of roughly constant duration between trials, but with situation-adapted amplitude. An interesting topic for further study is to investigate the exact perceptual cues that drivers use to determine the adjustment amplitude. Furthermore, a yaw rate nulling control law was found to explain much of the observed variability during stabilization steering. This phenomenon could be understood as a far point rotation nulling component of steering, proposed for example by Salvucci & Gray [140], coming to dominate in situations with large yaw rates.

Research question B: Is ESC equally useful for all drivers in realistic near-crash maneuvering?

It has been argued here that due to within-driver behavioral variability, this kind of individual-level question is difficult, if at all possible, to answer using empirical data collection and statistical analysis alone. Instead, it has been demonstrated how driver models fitted to behavior of individual drivers can be used to set up a simulation-based evaluation, where each recorded scenario is resimulated both with and without the system, with full repeatability in terms of initial conditions and driver behavior.

Using this approach, it was found that the ESC system was especially useful together with driver steering behavior that tended to cause large yaw instabilities without the system; in the simulations where maximum body slip angle with ESC off was above 10°, turning the system on reduced maximum body slip by 73 %, on average. For driver steering behavior leading to smaller yaw instabilities without the system, the benefits were smaller, and a trade-off was observed between the ESC system providing more efficient collision avoidance, and its natural result: a more difficult subsequent vehicle stabilization task. As a general rule, the driver models were still capable of controlling the situation, and there were no signs of any of the modeled drivers having consistent problems with the system. However, in a few simulations, potentially characterized by excessive driver steering in the collision avoidance phase, the outcome with the ESC system was markedly worse than without it. Some possible future ESC system improvements based on this finding, as well as on the yaw rate nulling phenomenon, have been discussed here, and preliminary development work has been carried out [109, 113].

One limitation of the computer simulations mentioned above was that while they did show an overall benefit of ESC, neither the absolute levels of body slip nor the relative effect of ESC closely matched the observations from the simulator study. This was possibly caused by the simulated drivers more often getting into severe skidding, due to small differences in the vehicle dynamics model, and the steering of the simulated drivers being somewhat slower than that of the human drivers. Nevertheless, the work on the ESC use case has arguably provided the best-validated model of near-crash stabilization steering to date, and quite certainly the most detailed investigation of individual differences in relation to an active safety system.

Research question C: For a given recorded rear-end crash, what would have happened if AEBS had been present?

Here, the aim was an initial sketch of a method, rather than a final answer. The proposed approach draws on previous simulation-based *what-if* evaluations of active safety, but it has also been emphasized that with access to increasingly detailed data about scenario kinematics and, especially, actual driver behavior before the crash, some modifications to the existing evaluation methods may be warranted. One part of these modifications is the use of a slightly different type of driver model, fitted to the specific crash event. Besides the currently ongoing development of such models, an important next step would be to compare the modified type of evaluation method (asking the question "how probable is it that *this specific crash* would have been avoided with the safety system?") to the existing methods (asking "how would the safety system have changed the probability of crash *in a general traffic situation with these kinematics*?"), to determine if and how the methods may differ in their estimates of system benefit.

Furthermore, regardless of the exact evaluation approach, it has been argued that the driver models used in previous what-if evaluations may have been overly simplistic, in assuming probability distributions of driver behavior to be essentially decoupled from the actual traffic situation. This concern motivated the fourth research question:

Research question D: Is the timing of drivers' defensive maneuvers in rear-end conflicts dependent on the specific situation kinematics, and, if so, how can this dependence be modeled?

Indeed, proof of kinematics-dependence was found in analysis of both existing test track data and naturalistic rear-end crashes and near-crashes. Specifically, it was found that the dependency could be understood and modeled using the concept of *evidence accumulation*, whereby an action is initiated after integration, up to a threshold, of evidence for the action's suitability. This model construct has been used in psychology and neuroscience to explain reaction time distributions and neural activity patterns in a wide range of experiments on signal detection and discrete decision-making [55, 134–136, 145]. However, to the author's knowledge, this thesis provides the first test of this construct as an explanation for timing of actual control actions in sustained sensorimotor control. Here, future research could be fruitful even at a much more basic level than vehicle driving. Within the context of driving, an important implication of the evidence accumulation hypothesis is that, in contrast with what has typically been assumed [88, 104, 122], there may not be any generally valid, kinematics-independent minimum thresholds for visual detection of collision obstacles.

To fully address the AEBS use case and research question C, also other driver model developments have been discussed, for example regarding how situation kinematics, active safety warnings, and interventions might interact to influence timing of control actions. Furthermore, the question of what determines drivers' general avoidance strategy in near-collision situations, i.e. the question of braking versus steering [3, 121], remains largely open. Here, preliminary indications have been found that one feasible modeling approach could be to consider braking and steering separately to some extent, and to model non-steering as the steering reaction being so late that collision, or successful conflict resolution by braking, occurs first.

6.2 Beyond the ESC and AEBS use cases

In Chapter 1, it was stated that the general aim of the present research work has been to "identify models that accurately describe near-crash driver behavior, in order to ensure validity of simulation-based active safety evaluations". One control question to ask might therefore be the following: To what extent has this been achieved for the ESC and AEBS use cases? Are the driver models proposed here accurate enough? Obviously, this depends on the exact research questions one is trying to answer, and it has been argued here that the models adopted in the ESC use case are accurate enough to allow the above answers to research questions A and B. However, if one wanted to answer a different question, such as "What exact reduction in accident frequency is to be expected from heavy truck ESC?", one would need to set higher standards, and for example look further into what caused the differences in ESC impact between the simulator study and the computer simulation.

With regards to the AEBS use case, it has been argued that the proposed kinematics-dependent reaction model is at least *more* accurate than current kinematics-independent models, but the exact impact of this improvement on what-if crash resimulations remains to be investigated. Again, the further one tries to generalize from relative effects in specific events, to absolute effects in entire crash populations, the more accurate driver models one is likely to need. It should be noted, however, that in the context of system development, a study of relative effects can often be enough: If system alternative A performs relatively better than system alternative B across a reasonably representative set of simulations, then one can prefer A over B even without estimates of their absolute safety effects.

Another control question that one could ask is: How do the models developed here fit into the greater context of simulation-based evaluation? How many of the most important near-crash driver behavior phenomena remain to be modeled? In relation to the ESC and AEBS use cases, this thesis has discussed (and in some cases proposed) models to account for: (i) the general choice of braking versus steering as collision-avoiding maneuvers, (ii) the timing and control of avoidance braking and steering, (iii) the effects of system warnings and braking interventions on collision-avoiding behavior, and, finally, (iv) control of steering during vehicle instability. Many of these behavioral phenomena are relevant also beyond the rear-end collision type of scenario studied here, such that models might be reusable. Depending on the scenarios and safety systems being addressed in future evaluations, one might also have to study and model for example: (v) the effect on collision avoidance of non-vehicle collision obstacles, such as vulnerable road users, (vi) the effect of lateral movement of collision obstacles, e.g. at intersections, (vii) gap acceptance at takeovers or when turning at intersections, or (viii) steering in response to lane or road departure (see [58] for a valuable contribution). The overall impression is that the research field is rapidly closing in on a point where rather good predictions of human behavior can be made in many of the most relevant near-crash scenarios. However, a persisting methodological concern is that comparisons and validations of existing models have been less frequent than proposals of new models.

Additionally, one may also need to consider behavioral aspects beyond the immediate near-crash situation, most notably relating to longer-term behavioral adaptation to support systems [147]. This seems especially relevant if one is aiming for absolute benefit estimates of the type discussed earlier. For example, it has been shown that the introduction of adaptive cruise control (ACC) and FCW can result in increased average time headways [74], something that could motivate a down-weighting of crashes with small initial headways in a what-if benefit evaluation of AEBS or similar systems, if the crash-involved vehicles were not equipped with ACC and FCW. Also adaptation in the opposite direction could occur, with drivers compensating for a perceived increase in vehicle safety performance by increased risk taking [171]. However, it is clear from the observed effects of past safety improvements that any such compensation is nowhere near complete [151].

Furthermore, future driver modeling should be put increasingly in contact with the strong trend of vehicle automation [56, 160, 162]. For example, the question of how driver control is influenced by and interacts with control supplied by the vehicle is currently a very active research field [1, 9, 123], into which many of the results of the present thesis can be fed. Another context where driver control modeling should be valuable is in simulated investigations of events where the automation reaches its capacity limits or experiences technical failure, so that the driver needs to intervene [54, 125].

Another possible direction of extension could be into biomechanical simulation of the driver's body during a crash, as a part of vehicle crashworthiness evaluation. In this area, the impact of driver posture and muscle tone is currently being given increasing attention [128], such that models of near-crash control behavior may become useful.

6.3 Modeling frameworks

In all of the future work that has been suggested in this chapter, driver modelers could benefit from the type of general modeling framework that was identified as a secondary research aim of this thesis. In the specific framework that has been sketched here, driver control is regarded as intermittent ballistic adjustments, triggered after noisy evidence accumulation of the deviation between current and predicted kinematics-related perceptual cues, together with anticipatory evidence of the need for adjustments. The kinematical perceptual cues are then also used in heuristics for determining adjustment amplitude, in a manner that is near-optimal within a non-critical, everyday driving regime. It has been argued here that such a framework can account for what otherwise seem to be contradictory characteristics of routine driving (closed-loop, short-latency, well-adjusted control) and near-crash driving (open-loop, long-latency, ill-adjusted control).

While some of the framework's assumptions have received initial experimental corroboration, all of them merit further testing and refinement: To what extent do drivers complement discrete burst-like control with longer and more smooth maneuvers, perhaps as learned superpositions of many consecutive bursts? Are there indications of evidence accumulation also in the timing of steering adjustments? Do the hypothesized heuristic mappings between perceptual cues and adjustment magnitudes exist, and if so what do they look like? Do they change with vehicle dynamics in the ways a mathematical treatment would suggest? Can signs of underlying forward-model prediction be found in drivers' closed-loop control of pedals and steering wheel? Furthermore, one can ask questions pointing towards possible extensions of the framework's scope: How do drivers acquire the putative sensorimotor heuristics, for example through reward-based learning [172]? How does top-down attention [34] or arousal affect evidence accumulation?

On the one hand, a search for answers to questions like those listed above can be motivated simply by sheer scientific curiosity and by a joy that hides, hopefully not completely, beneath the sentences in this thesis; the joy of coming to a better understanding of human cognition and behavior, even if slowly and ever so slightly. On the other hand, this thesis has also tried to make the point that in many cases, improved models of driver behavior are beneficial for industry and society as well, by enabling simulation-based evaluation as a cost-efficient complement to other test methods, by allowing more accurate estimates of the real value of active safety systems, by helping vehicle-makers to better tailor their systems to the human behind the steering wheel, and therefore in the end, hopefully, by contributing to safer vehicles and safer road traffic.

The sound of the collision warning rings in the truck cabin, and our driver has heard it often enough to reflexively and urgently shift her eyes towards the road. Indeed, a vehicle ahead of her looms closer, at an alarming rate, and neural activity in her brain quickly builds to a threshold at which her foot moves to the brake pedal. However, the afternoon is cold and the road is coated with a thin film of ice. When the situation does not resolve itself even when she is at almost full brake pressure, she glances towards the left mirror, finds the left lane open, and manages, with minimal margin, to steer away from the crash. However, once in the new lane the truck does not stop rotating as it should; it is going into a skid, and now the driver finds herself chasing the spinning outside world with her steering wheel, accompanied by the quick beating of air brake valves as the electronic stability control system kicks in. Seconds later, the truck has stabilized on the road, and continues ahead as if nothing special has happened. Our driver gives out a sigh of relief. That was a close call.

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Paper I

Effects of experience and electronic stability control on low friction collision avoidance in a truck driving simulator

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Effects of experience and electronic stability control on low friction collision avoidance in a truck driving simulator

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Abstract

Two experiments were carried out in a moving-base simulator, in which truck drivers of varying experience levels encountered a rear-end collision scenario on a low-friction road surface, with and without an electronic stability control (ESC) system. In the first experiment, the drivers experienced one instance of the rear-end scenario unexpectedly, and then several instances of a version of the scenario adapted for repeated collision avoidance. In the second experiment, the unexpected rear-end scenario concluded a stretch of driving otherwise unrelated to the study presented here. Across both experiments, novice drivers were found to collide more often than experienced drivers in the unexpected scenario. This result was found to be attributable mainly to longer steering reaction times of the novice drivers, possibly caused by lower expectancy for steering avoidance. The paradigm for repeated collision avoidance was able to reproduce the type of steering avoidance situation for which critical losses of control were observed in the unexpected scenario and, here, ESC was found to reliably reduce skidding and control loss. However, it remains unclear to what extent the results regarding ESC benefits in repeated avoidance are generalisable to unexpected situations. The approach of collecting data by appending one unexpected scenario to the end of an otherwise unrelated experiment was found useful, albeit with some caveats.

Keywords: driving experience, electronic stability control, trucks, collisions, driver behaviour, driving simulation

1. Introduction

Starting in 2014, electronic stability control (ESC) systems will be mandatory for all new heavy trucks in Europe (European Commission, 2011). One part of the upcoming ESC requirement is the inclusion of a yaw stability control (YSC) system, counteracting instabilities in the yaw plane, such as skidding on a low-friction road surface. YSC systems are designed to continuously monitor the vehicle's yaw rate, comparing it to a desired rate estimated from current steering wheel angle and speed. If the difference between the two becomes too large due to vehicle understeer or oversteer, the YSC system applies individual wheel brakes in a controlled manner so as to achieve appropriate yaw motion. Another required part of ESC systems is roll stability control (RSC), reducing vehicle speed when high lateral accelerations put the vehicle at a risk of roll-over.

For passenger cars, comparisons of crash statistics between ESC-equipped vehicles and non-ESC equipped vehicles have provided solid evidence that ESC prevents about 40% of control-loss crashes (Høye, 2011). For heavy trucks, however, such studies are not available, partially due to the currently limited deployment of ESC in trucks (Woodrooffe et al., 2009).

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Awaiting a possible impact of increased market penetration rates, other methods have been applied to estimate potential safety benefits of heavy truck ESC. Kharrazi and Thomson (2008) studied a U.S. in-depth database of 1,070 truck crashes and found that 18.7% of these involved loss of yaw or roll control, and could thus be targeted by ESC. Woodrooffe et al. (2009) combined a study of the same database with hardware-in-the-loop simulation and other methods, and were thus able to predict a prevention of around 4,700 out of an ESC-targeted annual U.S. crash population of around 11,000 (just over the 40% prevention ratio reported for passenger cars by Høye, 2011). Furthermore, tests with predetermined manoeuvres, specified in terms of exact control inputs or vehicle paths, have been carried out to provide verification of stability improvements of truck ESC, both in real vehicles driven by test drivers or steering robots (Laine et al., 2008) and in computer simulation (Kharrazi and Thomson, 2008; McNaull et al., 2010).

These previous research efforts provide important insights into the potential benefits of truck ESC, but one important factor, covered implicitly in the passenger car studies reviewed by Høye (2011), has to a large extent been left unaddressed: The actual behaviour of real drivers in the targeted critical situations, with and without ESC. In real traffic, drivers' control behaviour in an ESC-relevant situation can be expected to exhibit considerable between-driver *variability*, some of which will be due to limited *expectancy* for and limited *experience* of urgent manoeuvring. For example, limitations in expectancy and driving experience are both known to be associated with longer reaction times to hazards in a traffic scene (Deery, 1999; Green, 2000), and both factors may also influence the type of manoeuvring adopted by drivers in response to hazards, from highly controlled behaviours to non-reactions or overreactions (Malaterre et al., 1988; Hollnagel and Woods, 2005). Tests involving steering robots or skilled test drivers seem to hold limited validity in emulating these phenomena. In theory, driver models applied in computer simulation could be more successful in this respect, but so far available models generally lack proper validation (Markkula et al., in press).

A possible means of bridging this gap is the use of driving simulator studies. Although not free from validity concerns (e.g. in terms of fidelity of driver and vehicle behaviour to their real-traffic counterparts), simulator studies allow observation of ordinary drivers reacting to (reasonably) unexpected simulated critical situations. Papelis, Watson, Mazzae, and colleagues (Papelis et al., 2004; Mazzae et al., 2005; Watson et al., 2006; Papelis et al., 2010) conducted a series of large simulator studies on passenger car driving in unexpected scenarios designed to create vehicle instability, and consistently found that ESC reduced crash risk significantly. Dela et al. (2009) carried out a small pilot study of simulator-based testing of truck ESC, but found no effects of ESC. They argued that this could be due to their limited sample size.

In this paper, a simulator study will be presented that builds upon the study of Dela et al. (2009). The study presented here was focused on YSC specifically, in collision avoidance on a low-friction surface. This type of situation was adopted due to its presence in accident statistics (Kharrazi and Thomson, 2008, attribute 11% of truck control loss crashes to avoidance manoeuvres), in combination with the ample room it leaves for behavioural variability, implying that it could leverage well the specific advantages of simulator-based testing. Furthermore, due to the suspected impact of experience on avoidance behaviour, both novice and experienced drivers were included.

The overall aims were to study the effect of experience on when and how drivers responded to the situation, as well as the combined effects of experience and YSC on subjective and objective measures of situation outcome. Specifically, with regards to the YSC system, it was hypothesised that drivers would experience less severe skidding, and lower frequencies of full control loss, when the system was present. Furthermore, it was an aim of the study to clarify whether YSC would be equally helpful for drivers of both experience groups. In theory, if a driver's control strategies for critical manoeuvring, supposedly shaped by experience, differ from the YSC system's model of driver intentions, situations could arise where system and driver are pursuing slightly different goals. In order to investigate whether any detrimental mismatches of that kind could occur for either of the experience groups, interaction effects were hypothesised between experience and YSC presence, for measures of control effort and for situation outcome. With regards to other possible effects of driving experience on collision avoidance behaviour in this type of scenario, little was known beforehand, and therefore a more exploratory analysis approach was adopted.

Furthermore, two methodological devices were incorporated in the study, both aiming at more cost-

Table 1: *Parameters for the three versions of the critical lead vehicle braking scenario.*

Parameter	Unexpected	Repeated	Catch trial
R_x	1.15	1.15	1.15
T_{cut}	0.9 s	0.9 s	0.9 s
v_{cut}	5.4 km/h	5.4 km/h	5.4 km/h
T_b	1.5 s	1.5 s	1.5 s
d_b	0.35g	0.45g	0.45g
μ_1	0.7	0.7	0.7
μ_2	0.25	0.25	0.25
v_3	-	-	45 km/h
a_{acc}	-	-	0.3g

efficient collection of a larger data set for statistical analysis: (a) an *instruction-based* paradigm[1] for repeated collision avoidance, and (b) appending an unexpected critical scenario to the end of another simulator experiment. With regards to (a), it was hypothesised that the use of instructions would allow repeated reproduction of the type of steering avoidance situations that occur naturally in an unexpected scenario. With regards to both (a) and (b), exploratory analyses were carried out to clarify any impact these methodologies had on participant behaviour and situation outcome (effects of repetition, and of differing experiences prior to an unexpected situation, respectively).

The remainder of the text will be organized as follows: First, the adopted methods will be described, in terms of the conducted simulator experiments and the subsequent statistical analysis of obtained data. Then, results will be presented, followed by a discussion. Finally, some general conclusions will be provided.

2. Method

2.1. Simulator experiments

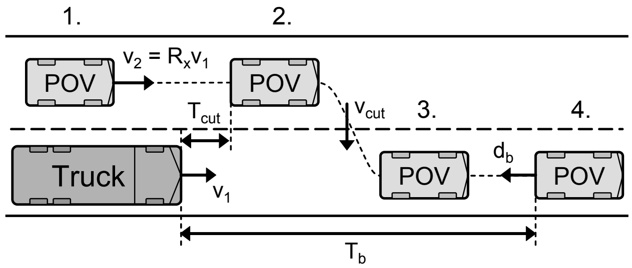
2.1.1. Simulated avoidance scenario

The simulated collision avoidance scenario was an adaptation of a scenario originally proposed by Engström et al. (2010); see Figure 1 for an illustration. The adapted scenario took place on a divided highway with 80 km/h speed limit, with two lanes in the truck's direction of travel. A passenger car, here referred to as the *principal other vehicle* (POV), overtook the truck at longitudinal speed $v_2 = R_x v_1$ proportional to the truck's current longitudinal speed v_1. Then, at a time headway of T_{cut} with respect to the truck, the POV changed into the truck's lane, at lateral speed v_{cut}, and continued ahead at longitudinal speed v_2. Then, for no apparent reason, at time headway T_b, the POV applied braking with a longitudinal deceleration d_b. Prior to this deceleration, the POV's longitudinal speed was set, from one simulation time step to the next, to the truck's speed v_1. This was done to ensure that as soon as POV brake lights were turned on, time headway would start decreasing below T_b. Before the start of the scenario, road friction was at a value μ_1, corresponding to dry asphalt. During the scenario, a lower value μ_2 was set, to emulate a wet or icy road surface. The visual representation of the road scene did not change, however, so the drivers had no indication that friction had been reduced.

As indicated in Table 1, this scenario was parameterised in three different versions, an *unexpected avoidance* version, a *repeated avoidance* version, and a *catch trial* version. In the first two versions, braking alone was not enough to avoid collision with the POV (i.e. steering was needed). In the catch trial version, however, POV deceleration ended at longitudinal speed v_3, and was followed by a longitudinal acceleration a_{acc}, such that the truck driver could avoid a collision by braking only.

The aim of the unexpected avoidance version of the scenario was to elicit *ESC-relevant manoeuvring* from unexpecting drivers, for as many as possible of the participants. ESC-relevant manoeuvring is here defined

[1] Here, an instruction-based paradigm is one in which drivers are given some prior instructions on how to behave in response to the simulated scenarios.



(a)

(b)

Figure 1: *(a) Schematic illustration of the simulated avoidance scenario. After Engström et al. (2010). (b) A still from the recorded video data, showing the winter environment in which the simulated avoidance scenario took place, and a driver engaged in steering avoidance.*

as manoeuvring that triggers an ESC yaw control intervention, or would have triggered such an intervention, had the ESC system been active[2]. For this to occur in practice in the avoidance scenario studied here, a steering avoidance manoeuvre of some severity is typically needed (as opposed to e.g. braking only, or a moderate steering manoeuvre). A pilot study was carried out: In a fixed-base driving simulator, twenty-five professional truck drivers experienced, at the end of another simulator experiment, one of six scenario parameter combinations varying T_b and d_b. The parameter combination for which the highest frequency of severe steering avoidance was observed is the one adopted here.

The aim of the repeated avoidance and catch trial versions (used together as described in the next Subsection) was to recreate in repeated avoidance roughly the same lateral avoidance situation as in unexpected avoidance, in terms of vehicle speeds, headway, and time to collision at the time of steering initiation. To this end, values for d_b and v_3 were chosen based on results of simulations with a simple driver–vehicle model, assuming reaction times to unexpected stimuli as observed in the pilot study, and to expected stimuli as suggested by Green (2000).

[2]Specifically, a manoeuvre is considered ESC-relevant if the difference between the actual yaw rate of the truck and the driver's desired yaw rate (calculated based on vehicle speed and steering wheel angle) exceeds a certain threshold value at any point during the manoeuvre. This is a simplified version of the triggering criterion of the actual ESC system used in this study, but in preliminary tests it was found that this method predicted reliably whether or not a given manoeuvre would trigger an ESC yaw control intervention.

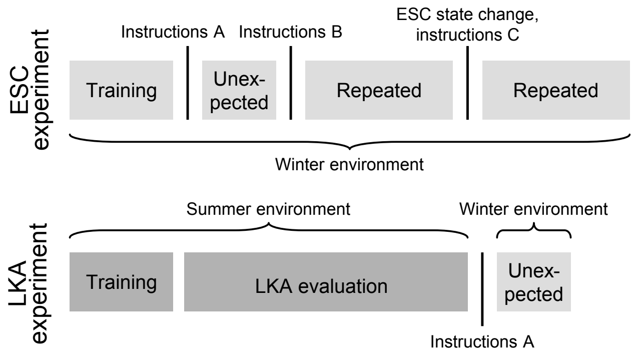


Figure 2: *An overview of the experimental procedure used in this study. Further details are provided in the text.*

2.1.2. Experimental procedure

An overview of the experimental procedure is provided in Figure 2. Data were collected from two simulator experiments, here referred to as the *ESC experiment* and the *lane keeping assistance (LKA) experiment*. Both experiments started with standard procedures for obtaining subject consent. However, nothing was said to the subjects regarding ESC or critical situations, in order to limit expectancy of such situations as much as possible.

The ESC experiment started with a ten-minute training drive, on the same two-lane highway as in the avoidance scenario described above. Inspired by Jamson and Smith (2003) and McGehee et al. (2004), the training drive included both steady state driving, with surrounding (overtaking) traffic, as well as five decelerations to full stop from 80 km/h, and six lane changes.

Unexpected avoidance: Next, subjects were instructed that their first task was now to drive normally at 80 km/h until instructed otherwise, and that this part of the experiment would last less than ten minutes ("instructions A"in Figure 2). After about four minutes of driving, including four overtaking vehicles and one lane change induced by a roadwork site, the unexpected avoidance scenario occurred. At this point, half of the subjects had the ESC system present, and half did not. This division was also balanced across experience groups (see section 2.1.4). However, all subjects had an anti-lock braking system (ABS). After the scenario, the subjects were asked to assess the severity of the resulting situation.

Repeated avoidance: Next, some information and instructions were provided ("instructions B" in Figure 2). Subjects were informed of the presence of ABS and the presence or absence of ESC (explained as an "anti-skid system")[3]. They were also informed that in the following, overtaking cars would sometimes brake in front of them, and that in a majority of cases braking alone would be sufficient to avoid collision (the catch trial scenario), but that sometimes it would not (the repeated avoidance scenario). In the latter cases, drivers were instructed to apply evasive steering. In a first block, subjects experienced a randomised sequence of 18 events: four overtaking vehicles, eight instances of the catch trial scenario, and six instances of the repeated avoidance scenario. Each repeated avoidance scenario was followed by the subjects assessing situation severity. After completion of this block, the ESC state was changed from off to on or vice versa. Subjects were informed of this change ("instructions C" in Figure 2), and finally experienced another block, identical to the first one except for the randomized order of scenarios.

The main purpose of the LKA experiment (described in more detail by Johansson et al., 2012) was to study a lane keeping assistance function, providing warnings or steering torque control interventions in the case of lane excursions without prior turn indication. Here, the training drive and the main experiment (together about 30 minutes total driving time) took place on a rural road in a summer setting. During the experiment, drivers carried out a visual-manual secondary task, and vehicle dynamics was manipulated so

[3]The argument behind informing on the presence or absence of the ESC system was that not doing so could introduce additional variance in subject behaviour, if some drivers were able to notice system presence and some were not.

Table 2: *Summary data on the subjects included in the experiments of this study.* License *refers to license for heavy truck with trailer. Kilometers driven refers to driving with heavy truck.*

Experiment	Experience	N	Gender		Age			Years w. license			10^3 km driven/year		
			M	F	Av.	S.D.	Range	Av.	S.D.	Range	Av.	S.D.	Range
ESC	Low	12	9	3	22	6	18-35	0.6	1.0	0-3	20	35	0-100
	High	12	12	0	46	9	32-60	22	10	6-40	60	46	4-150
LKA	Low	8	7	1	21	7	18-37	0	0	0	14	39	0-110
	High	16	16	0	45	10	28-61	20	13	4-43	96	32	45-160

as to generate lane excursions, thus allowing drivers to experience and subjectively assess the LKA system. At the end of the experiment, the simulated truck was moved to the winter driving environment used in the ESC experiment, drivers were provided with the same initial instructions as the ESC experiment drivers, and then experienced an identical unexpected avoidance block.

2.1.3. Driving simulator

The *VTI Driving Simulator II* in Linköping, Sweden, was used for both the ESC and LKA experiments. It consists of a truck cabin and a visual system mounted on a motion platform. The visual system provides a 105° forward field of view, and rear view mirrors are emulated using LCD displays. The motion platform provides linear motion of ± 3.5 m (in this study used to emulate lateral movement of the simulated truck), as well as pitch and roll motion.

Vehicle dynamics were emulated using a Volvo in-house model of a six-wheeled rigid truck with a wheel base of 6.2 m, from first to last axle. The brake control system, including ABS and ESC, was emulated by an exact software-in-the-loop integration of the software used in actual Volvo trucks. The resulting simulated vehicle dynamics during low-friction manoeuvring were subjectively judged as acceptable by experienced test drivers, and inspection of data recorded from the simulator indicated a qualitative match between the simulated truck's behaviour and that of its real life counterpart in similar manoeuvres (Markkula et al., 2011). Limited quantitative validation was obtained by verifying that the simulated vehicle's yaw rate response to a step steering input on a high-friction road surface reproduced closely that of the real truck. Furthermore, the sound of air release from the pneumatic brake chambers was emulated, to provide auditory feedback on ongoing ABS and ESC interventions.

To ensure safety of subjects, the simulation was aborted whenever the there was a risk of the motion platform reaching the physical endpoints of lateral motion. In practice, this meant that full road departures could not be observed; see further Section 2.2.2.

2.1.4. Subjects

Table 2 provides summary data on the subjects involved in this study, separately for the two experiments and the two experience groups. Low-experience drivers were recruited mainly from a local driving school. They had a license to drive a heavy truck, and had just recently or was just about to obtain a license to drive a heavy truck with a trailer. High-experience drivers were recruited from local hauler companies.

The ESC experiment involved 24 subjects, divided equally into the two experience groups. The LKA experiment also had 24 subjects, originally divided into three experience groups *low*, *medium* and *high*, where the two latter groups taken together corresponded to the *high* group of the ESC study. For the purposes of this study, the *medium* and *high* groups of the LKA study were thus merged into one group, denoted *high*.

2.2. Experimental design

2.2.1. Independent variables

The independent variables considered in this study were: (a) *Driving experience*, with conditions *low* and *high*, defined as in Table 2. (b) *ESC state*, with conditions *on* and *off*. (c) *Test setting*, with conditions *unexpected*, *repeated* (both referring to the ESC experiment) and *unexpected after LKA* (referring to the LKA experiment). (d) *Repetition*, with conditions *1* through *12*, or *1* through *6*, when analysing repetitions with ESC state on and off separately.

2.2.2. Dependent variables

As mentioned above, after each avoidance event, both in the unexpected and repeated test settings, subjects were asked to rate the resulting severity of the event, on a scale from one to ten (from *"there was no danger at all"* to *"there was a serious accident"*). The severity of the situation in terms of vehicle stability was also quantified objectively, using the measure *maximum body slip angle* (defined as the maximum deviation between the direction of the truck's front and the truck's direction of motion, see Figure 5 for an illustration), as well as the binary measures *ESC-relevant manoeuvring occurred* (see Section 2.1.1 for a definition) and *full control loss occurred*.

Full control loss was defined as occurring whenever either or both of the following occurred: (1) loss of directional control, or (2) road departure beyond either road shoulder. For determining loss of directional control, the algorithm proposed by Papelis (2006) was adopted. This algorithm reports loss of directional control whenever the maximum body slip angle exceeds 45 degrees, the terminal yaw angle compared to the road at simulator safety system intervention (see Section 2.1.3) exceeds 45 degrees, or the terminal yaw rate exceeds 20 degrees per second[4]. This algorithm was tuned for passenger cars, but its judgments correlated very well with our subjective judgments of loss of directional control also for this data set. As previously mentioned, road departure could not be observed directly, since the simulators safety system aborted simulation before full road departure occurred. For four instances of repeated on-road avoidance, the safety system intervened without directional control loss being reported by the algorithm of Papelis (2006). Based on inspection of video logs and terminal lateral position, yaw angle and yaw rate data, it was subjectively judged that road departure beyond a road shoulder would have occurred in three out of these four instances, had the simulation not been aborted. The fourth case was less certain, and was therefore not classified as a full control loss.

To capture the steering effort applied in vehicle stabilisation, the measure *steering wheel reversal rate* was calculated, using the implementation proposed by Markkula and Engström (2006), with *gap sizes* 5° and 20°. This measure took into account steering data recorded from the point of reaching the POV (defined as the truck's front longitudinally reaching the rear of the POV, with or without collision), to whichever occurred first of: (a) the truck travelling 100 m after reaching the POV, (b) the truck's speed falling below five km/h, or (c) full control loss.

In addition to the above-mentioned dependent measures, motivated by the specific hypotheses defined in Section 1, additional objective measures were defined to allow a more detailed, exploratory study of the braking and steering control applied by the drivers in response to the collision situation.

Brake reaction time was calculated as the time from POV brake light onset to the first instant with a non-zero depression of the truck's brake pedal (signal confirmed to be noise-free, in this respect). Similarly, *steering reaction time* was calculated as the time from POV brake light onset to the moment of *steering initiation*, defined as the first instant with an absolute steering wheel angle exceeding 15°. Drivers who did not reach this threshold value were classified as non-steering[5]. Furthermore, to obtain a quantitative description of the situation at first steering, the measures *longitudinal speed at steering initiation* and *time to collision (TTC) at steering initiation* were calculated. Throughout this paper, TTC is defined as headway distance divided by relative speed (i.e. accelerations are disregarded). Evasive braking behaviour before reaching the POV was quantified using the measures *maximum brake pedal position* and *maximum brake pedal speed*, and to quantify the initial leftward evasive steering (all steering drivers evaded to the left), the measures *maximum leftward steering wheel angle* and *maximum leftward rate of steering* were calculated, also using only data from before reaching the POV. The severity of the collision situation was quantified using the measure *minimum TTC* (defined as TTC at the instant just before the truck steered clear of the POV, laterally), as well as the binary measure *collision occurred*.

[4]Papelis (2006) also included criteria based on excessive yaw angles at reaching zero speed, and detection of the vehicle traveling backwards, but such outcomes did not occur in this study.

[5]The 15° threshold was adopted based on the observation that the smallest maximum steering wheel angle applied by any driver who was able to avoid collision with the POV was 17°. More elaborate algorithms for identifying the time of steering initiation were also tested, but yielded similar results as those reported further below for the 15° threshold approach, therefore preferred here for its simplicity.

2.3. Statistical analysis

For all dependent variables except the binary variables, general linear model (GLM) analysis of variance (ANOVA) was used to test for effects of the independent variables. For the dependent measures which were meaningful only in cases where the subjects applied evasive steering (steering reaction time, and the measures quantifying the situation at steering initiation), non-steering events were treated as missing values, with listwise deletion. The data from the two unexpected avoidance settings were analysed using between-subjects ANOVA, with a full factorial model *test setting* (only including levels *unexpected* and *unexpected after LKA*) $\times$ *experience* $\times$ *ESC state*. The repeated avoidance data were analysed using mixed design ANOVA, with a full factorial model *experience* $\times$ *ESC state* $\times$ *repetition*. To compare the unexpected and repeated test settings, per-driver averages of the repeated avoidance data were taken, and mixed design ANOVA *experience* $\times$ *test setting* (only including levels *unexpected* and *repeated*) was carried out[6].

To analyse binary dependent variables (such as *collision occurred*, or *full control loss occurred*), two types of tests were used: For the unexpected avoidance data, χ^2 tests (replaced with Fisher's exact test when expected frequency in any cell was below 5) were carried out for each independent variable separately. For the repeated avoidance data, binary variables were transformed to continuous variables by taking averages, per driver and ESC state, yielding measures such as *control loss frequency*. Mixed design ANOVA *experience* $\times$ *ESC state* was then carried out on these measures.

When there were indications that ANOVA assumptions were not met (Shapiro-Wilks test of normality, Levene's test of variance homogeneity, and Mauchly's test of sphericity), the ANOVAs were replaced by non-parametric tests (the Mann-Whitney test for between-subject factors, Friedman's ANOVA for the twelve-level *repetition* factor, and the Wilcoxon signed-rank test for the other, two-level, within-subject factors). In general, non-parametric testing was applied to the same data sets as would have been used for the ANOVAs. However, in one specific case (the analysis of the effect of ESC state on max body slip in the repeated avoidance data), averaging per driver and ESC state, such as outlined above for binary variables, was applied in order to be able to apply the Wilcoxon signed-rank test.

It should be noted that the statistical modelling and testing described above served the dual purpose of analysis outlined in Section 1: (a) testing a number of specific hypotheses, and (b) exploring other effects of the independent variables on driver behaviour and situation outcome. Due to the large number of statistical tests carried out, there is a clear risk of committing Type I errors if one interprets results solely in terms of statistical significances (here, $p < 0.05$ or lower). In response to this concern, the significance testing was complemented with calculation of effect sizes, in terms of Pearson's correlation coefficient r (as recommended by Field, 2009, here possible to apply for all of the independent variables except repetition, since it had more than two levels), and special care will also be taken when discussing the results in Section 4.

3. Results

Overall, 48 instances of unexpected collision avoidance were recorded, and $24 \times 2 \times 6 - 1 = 287$ instances of repeated avoidance (in one case, the repeated avoidance scenario was terminated prematurely, due to an unintended effect of the scenario programming). Figure 3 shows the obtained vehicle trajectories.

In what follows, notation with regards to statistical testing is to be interpreted as follows: F-values refer to GLM ANOVAs, U-values refer to Mann-Whitney tests, T-values to Wilcoxon signed-rank tests, and χ^2-values refer to χ^2 tests if not otherwise indicated (in some cases, they refer to Friedman ANOVAs). In all figures showing bar charts, error bars show 95% confidence intervals, calculated under the assumption of a normal sampling distribution.

[6]The averaging approach reduces the power of the statistical testing, but was preferred over adoption of more elaborate statistical methods, which would be required in order to handle the major difference in sample size between unexpected and repeated test settings in the original data set.

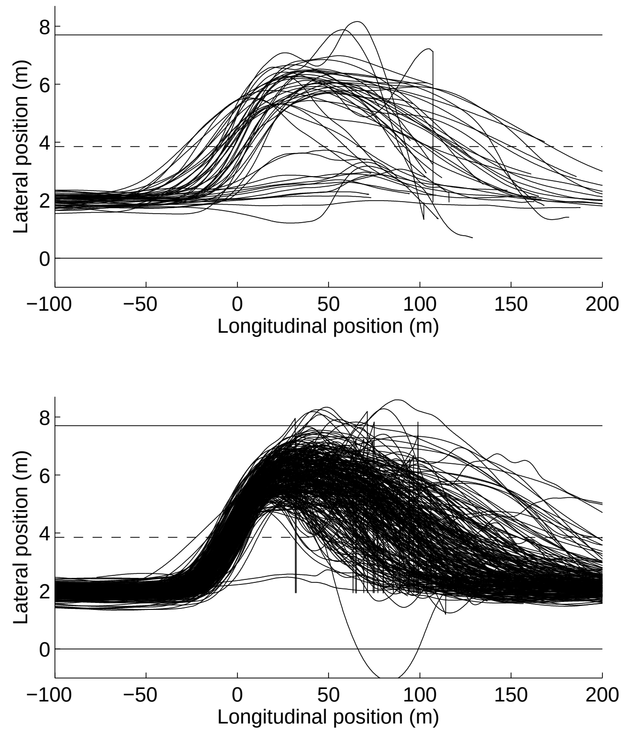


Figure 3: *Recorded vehicle trajectories for unexpected (top panel) and repeated (bottom panel) collision avoidance. Horizontal lines indicate lane boundaries. Longitudinal position zero corresponds to the point where the truck front reached the rear of the lead vehicle.*

3.1. Unexpected collision avoidance

The unexpected scenario gave a varied range of behavioural responses and situation outcomes. 11 drivers out of the 48 (23%) did not apply evasive steering (i.e. had maximum steering wheel deflections below 15°; see Section 2.2.2). In all these cases, the drivers collided with the POV. The timing, magnitude, and outcome of the evasive steering behaviour applied by the remaining 37 drivers is illustrated in Figure 4. In total, collision occurred for 25 of the 48 drivers (52%). ESC-relevant manoeuvring was observed for nine of the drivers (19%) and, out of these, three experienced full control loss (one with ESC inactive, two with ESC active). A more detailed view of control behaviour and the resulting vehicle trajectories is provided in Figure 5, for three drivers: One who did not steer, one who successfully avoided the near-collision situation, and one who experienced full control loss.

Figure 6 illustrates the main results regarding driving experience in the unexpected scenario, separated into the data collected from the ESC and LKA experiments: Experienced drivers had significantly shorter brake reaction times ($U = 163.0$, $z = -1.99$, $p < 0.05$, $r = 0.29$; Figure 6a), and applied significantly less braking, in terms of maximum brake pedal position ($F(1, 40) = 5.82$, $p < 0.025$, $r = 0.36$; not shown in figure; averages were 80% and 59% of maximum brake pedal position, for low and high experience drivers, respectively). Regarding whether or not evasive steering was applied, there was no statistically significant effect of experience (Fisher's exact test, $p > 0.05$, $r = 0.14$; Figure 6b), but among the drivers who did attempt steering, the reaction times to steering were significantly shorter for experienced drivers ($F(1, 29) = 10.10$, $p < 0.01$, $r = 0.51$; Figure 6c; the lower number of degrees of freedom in this specific test is due to the exclusion of non-steering drivers, see Section 2.3). Furthermore, the overall frequency of collisions was significantly lower among experienced drivers than among inexperienced drivers ($\chi^2(1) = 10.71$, $p < 0.01$, $r = 0.47$; Figure 6d).

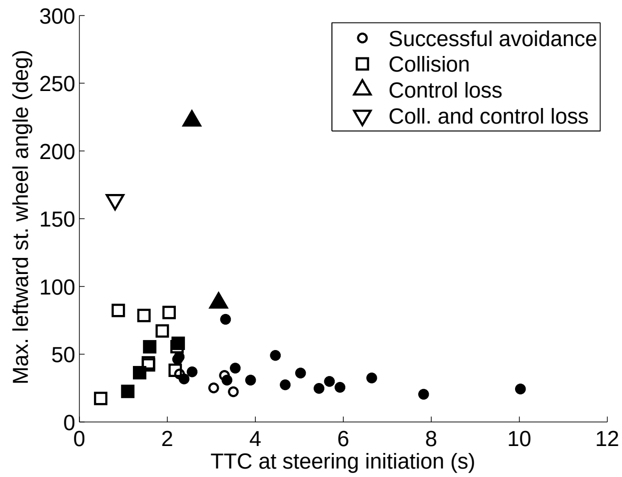


Figure 4: *Outcome of the unexpected scenario, for drivers who attempted steering, as a function of when and how steering was applied. (For all drivers who did not attempt steering, the outcome was a collision.) Filled and empty symbols denote drivers from the high and low experience groups, respectively.*

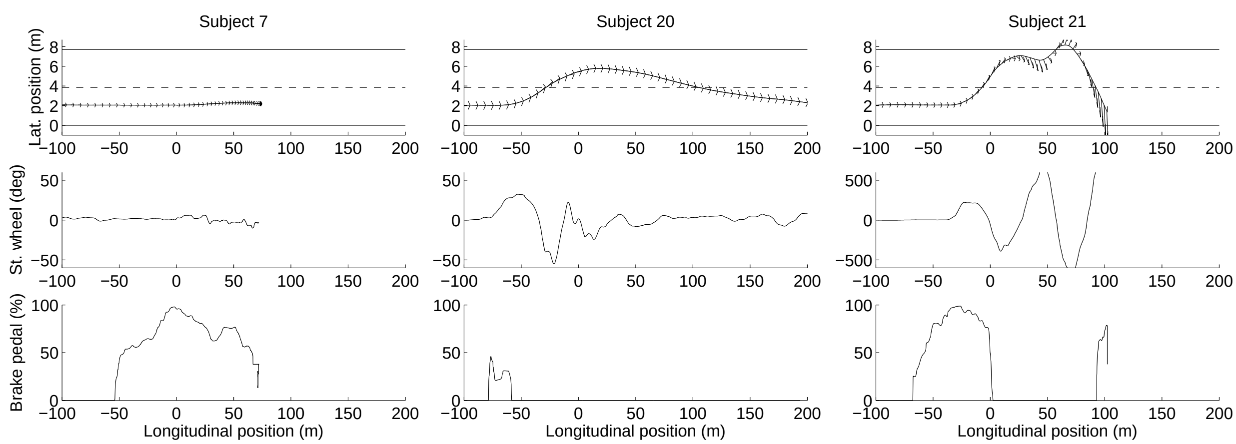
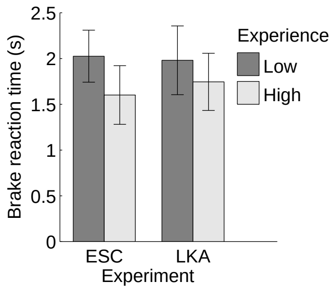
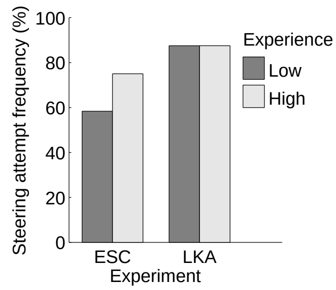


Figure 5: *Recorded vehicle trajectories (top panels), steering input (middle panels, note the variations in scale), and brake input (bottom panels), for three selected drivers in the unexpected avoidance scenario. In the top panels, horizontal lines indicate lane boundaries, and the arrows along the trajectories show momentary direction of the truck's front (i.e. indicate skidding, or* body slip, *when pointing away from the trajectory). Subject 7 collided with the lead vehicle at longitudinal position zero (corresponding, for all drivers, to the point where the front of the truck reached the rear of the lead vehicle), subject 20 managed a successful collision avoidance, and subject 21 reached full control loss (see the text for definition) at about 100 m longitudinal position.*



(a)



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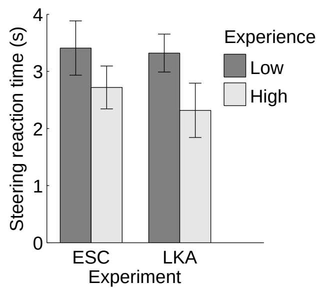
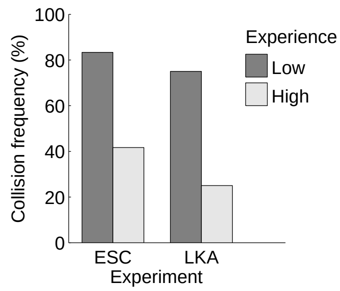


(c)



(d)

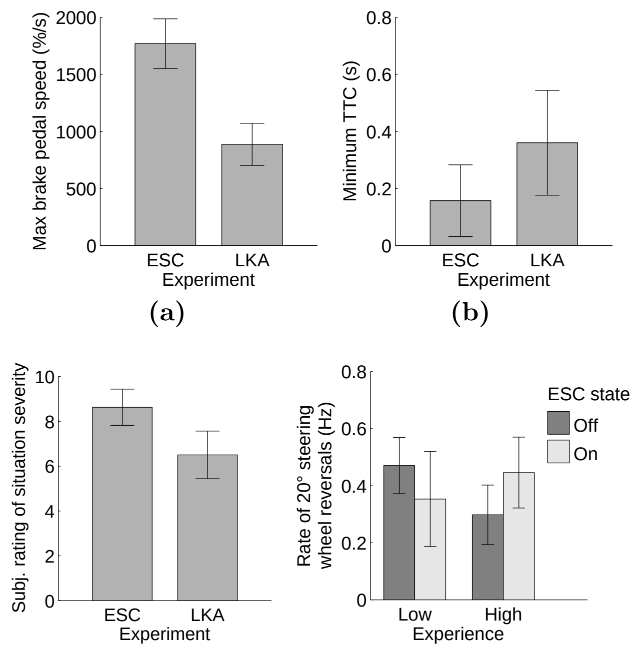
Figure 6: *Effects of driving experience on avoidance reactions and collisions in the unexpected avoidance scenario, observed in the two experiments involved in this study.*

None of the differences between the ESC and LKA experiments shown in Figure 6 were statistically significant, providing some motivation for analysing the two data sets together with respect to the dependent variables shown in the figure; this issue will be discussed further in Subsection 4.3.1. However, there were also some statistically significant effects, illustrated in Figure 7: The LKA experiment drivers used significantly lower brake pedal speeds ($F(1, 40) = 31.92$, $p < 0.001$, $r = 0.67$; Figure 7a), had significantly higher minimum TTCs ($U = 192.0$, $z = -1.98$, $p < 0.05$, $r = 0.29$; Figure 7b), and rated the severity of the situation significantly lower than the ESC experiment drivers ($U = 140.5$, $z = -3.10$, $p < 0.01$, $r = 0.48$; Figure 7c).

In the unexpected scenario, no statistically significant effects of the state of the ESC system were observed on any of the dependent measures. However, for steering wheel reversal rate, there was a significant interaction between ESC state and driving experience: For inexperienced drivers, average reversal rates were lower with the ESC system active than without, whereas for experienced drivers the opposite was observed, both for 20° gap size ($F(1, 40) = 4.32$, $p < 0.05$; shown in Figure 7d) and 5° gap size.

3.2. Repeated collision avoidance

Steering avoidance attempts were observed in 285 out of the 287 instances of repeated avoidance (99%), and ESC-relevant manoeuvring (as defined in Subsection 2.1.1) occurred in 217 of 287 instances (76%). Here, some significant effects of the ESC system could be observed, see Figure 8. With ESC active, the maximum body slip angle was reduced ($T = 57$, $p < 0.01$, $r = 0.38$; analysis included averaging over repetitions, as described in Section 2.3; Figure 8a), and so was the per-driver frequency of full control loss ($T = 0$, $p < 0.001$, $r = 0.45$; Figure 8b). These analyses were carried out non-parametrically, due to violations of ANOVA assumptions, and therefore the hypothesised interactions for these measures, between ESC state and driver experience (see Section 1) could not be tested directly. Instead, additional non-parametric testing was carried out for the two experience groups separately. In this analysis, the effect of ESC on maximum



(a) (b) (c) (d)

Figure 7: *(a)–(c): Effects of experiment on behaviour and outcome in the unexpected collision avoidance scenario. (d) An interaction effect, of driving experience and ESC state, on large steering wheel reversals in the stabilisation phase of unexpected collision avoidance.*

body slip angle was found significant for inexperienced ($T = 11$, $p < 0.05$, $r = 0.45$) but not for experienced drivers ($T = 18$, $p > 0.05$, $r = 0.34$), whereas the effect on control loss frequency was significant for both experience groups ($T = 0$, $p < 0.05$, in both cases; $r = 0.45$ and $r = 0.46$ for low and high experience, respectively). There were no significant interactions of ESC state and driving experience for any of the other dependent measures, e.g. the interaction effect for steering wheel reversal rate observed for the unexpected scenario was not observed for the repeated scenario.

Figure 9 illustrates the main findings regarding similarities and differences between unexpected and repeated avoidance behaviour. In terms of braking, there were clear differences. The average brake reaction time was significantly lower in the repeated setting than in the unexpected setting ($F(1, 22) = 98.79$, $p < 0.001$, $r = 0.90$; Figure 9a), and the maximum brake pedal position was significantly higher in the repeated setting ($T = 36$, $p < 0.01$, $r = 0.47$; shown in Figure 9b). However, the near-collision situation facing drivers at the moment of steering initiation was not significantly different between unexpected and repeated settings, in terms of longitudinal speed ($F(1, 14) = 1.54$, $p > 0.05$, $r = 0.31$; Figure 9c) or TTC ($F(1, 14) = 0.52$, $p > 0.05$, $r = 0.19$; Figure 9d)).

In the repeated avoidance data, there were some effects of repetition itself. The maximum brake pedal position gradually increased over repetitions (Friedman ANOVA $\chi^2(11) = 32.61$, $p < 0.01$; Figure 10a). Likewise, the significant effects of repetition on brake reaction time (Friedman ANOVA $\chi^2(11) = 55.77$, $p < 0.001$; Figure 10b) and subjectively perceived situation severity (Friedman ANOVA $\chi^2(11) = 55.77$, $p < 0.001$; Figure 10c) could possibly be interpreted as gradual trends, but the significant effect of repetition on the 20° steering wheel reversal rate (Friedman ANOVA $\chi^2(11) = 24.47$, $p < 0.025$; Figure 10d) was less clearly gradual in nature. There were no significant effects of repetition on the objective measures quantifying situation outcome severity.

4. Discussion

The main results of this study are (a) the effects of driving experience in the unexpected scenario, and (b) the effects of ESC state, especially in the repeated scenario. Below, these two matters are discussed separately. Furthermore, a brief discussion regarding methodological aspects is given. For the reasons outlined in Subsection 2.3, the discussion will not rely solely on levels of statistical significance, and especially so for the more exploratory statistical analyses.

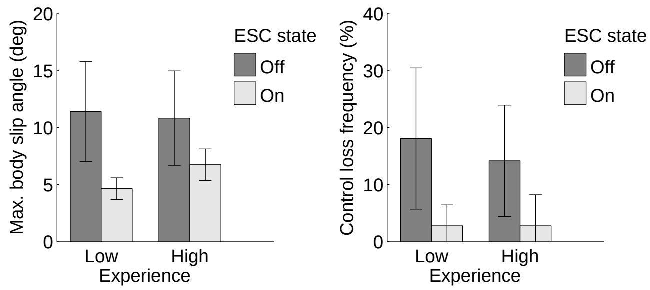
4.1. Impact of driving experience on unexpected avoidance

As illustrated in Figure 6d, in the unexpected critical scenario of this study, the inexperienced drivers were significantly less successful than the experienced drivers at avoiding collision with the POV. Below, possible explanations for this finding are discussed.

4.1.1. Differences in reaction times

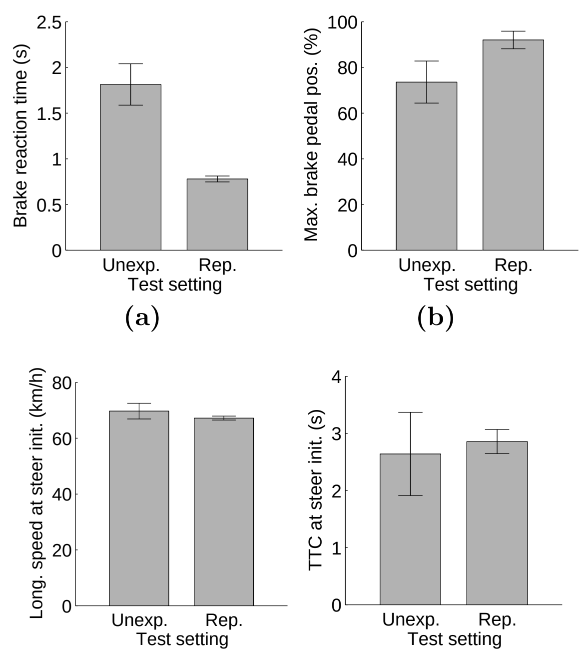
First of all, the inexperienced drivers had significantly longer brake reaction times (Figure 6a). This medium sized effect ($r = 0.29$; the denominations of effect sizes proposed by Cohen, 1988, are adopted here) aligns well with previous empirical results. Novice drivers have repeatedly been found to be slower than more experienced drivers at detecting and responding to hazards in a traffic scene, and it has been proposed that this may, for example, be due to a poorer ability of context-sensitive anticipation of possible hazards, and less efficient visual scanning strategies (see e.g. Deery, 1999; Scialfa et al., 2011).

However, in the unexpected critical scenario of this study, braking alone was not sufficient to avoid a collision, regardless of brake reaction time. Successful crash avoidance thus depended crucially on the use of evasive steering. Despite the fact that there was ample margin for safe steering avoidance (e.g. as illustrated by subject 20 in Figure 5), 52% of drivers failed to apply steering successfully. Also these results are in line with previous observations, from both accident studies and controlled experiments (Adams, 1994; Lechner and van Elslande, 1997), and it has been suggested that this type of reluctance or inability to apply required evasive steering may be due to drivers' limited experience of severe lateral manoeuvring, or to perceived added risks of rapidly leaving one's own lane.



(a) **(b)**

Figure 8: *Effects of ESC state on skidding and control loss in the repeated avoidance scenario. It may be noted that the control loss frequency data was significantly non-normal, which is evident here from the confidence intervals of Panel (b) extending below zero. As mentioned in the text, confidence interval calculations assumed normality, but the statistical analyses did not.*



(a) **(b)** **(c)** **(d)**

Figure 9: *Comparison of unexpected and repeated avoidance. Note that the averaging approach described in Subsection 2.3 reduces the contribution of intra-driver variance to the total variability in the repeated avoidance setting, something that affects the confidence intervals shown here.*

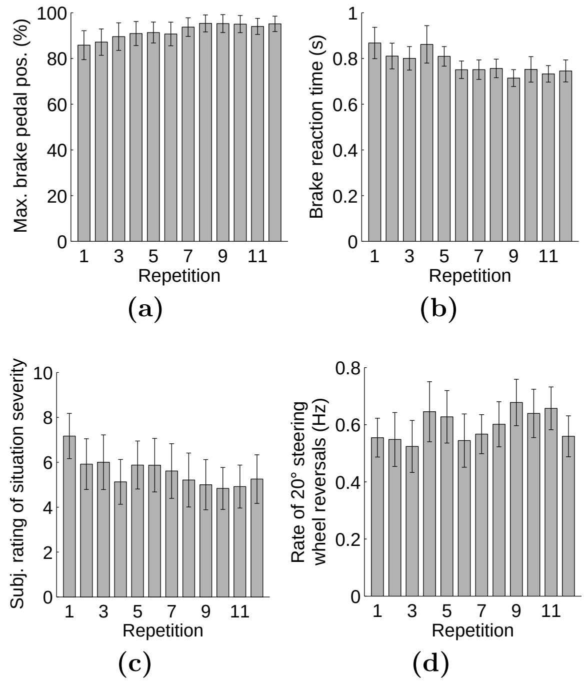


Figure 10: *Effects of repetition on braking behaviour and skidding in the repeated avoidance scenario.*

Overall, Figure 4 suggests that the main reason for failed steering avoidance in this study was that initiation of steering occurred *too late*. In a rear-end collision situation, there will typically be a point in time after which steering avoidance is no longer possible, for the given vehicle on the given road surface. Here, Figure 4 shows clear indications of such a limit being present at a TTC of around two seconds: All drivers initiating steering at a TTC below this limit collided with the POV, regardless of the amount of steering applied, and all drivers initiating steering earlier were able to avoid collision.

Thus, if a late steering initiation is the main cause of collisions in the unexpected scenario, the large effect ($r = 0.51$) of experience on steering reaction time, with later steering responses for inexperienced drivers (Figure 6c), may be considered a satisfactory explanation for the more frequent collisions suffered by these drivers.

4.1.2. Alternative explanations

Two alternative explanations could be that (a) in a given situation, inexperienced drivers apply smaller steering magnitudes than experienced drivers, such that steering is more often insufficient to avoid the collision, or (b) experienced drivers are more prone than inexperienced drivers to attempt a steering manoeuvre at all. However, none of these explanations seem to be clearly supported by the recorded data.

With regards to (a), there were no significant effects of experience on maximum steering magnitudes or rates; in the unexpected scenario the average maximum steering magnitudes were actually slightly higher for inexperienced drivers than for experienced drivers. Furthermore, any between-driver differences regarding whether or not sufficient steering was applied should have been visible in Figure 4, as regions of TTC at steering initiation within which some drivers avoided collision, whereas other drivers applied less steering and did not avoid collision. In other words, there should not have been such a sharp limit of TTC beyond which all drivers collided.

With regards to (b), the frequency of attempted steering was indeed lower for inexperienced than for experienced drivers (70% versus 82%; Figure 6b), but this small effect ($r = 0.14$) was not statistically

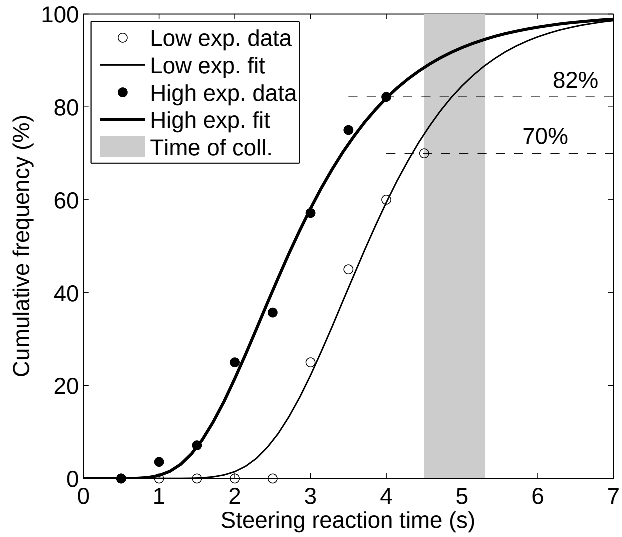


Figure 11: *Least-squares fit of log-normal cumulative distribution functions to cumulative steering reaction time data for the drivers who attempted steering in the unexpected scenario (70% and 82% of low and high experience drivers, respectively). The shaded region shows the range of time after lead vehicle brake initiation within which all observed collisions occurred.*

significant. In any case, further analysis suggests that this alternative explanation can to some extent be reconciled with the proposed explanation in terms of reaction times: Figure 11 suggests that both the obtained steering reaction time data *and* the observed frequencies of non-steering can be interpreted as due to the same log-normal distributions of steering reaction time (one for each experience group), cut off at the point where collision occurred. According to this interpretation, the non-steering drivers should not be understood as drivers who would *never* apply steering avoidance, but instead as drivers with a long enough steering reaction time for collision to occur before steering initiation.

4.1.3. Mechanisms governing steering reaction times

An obvious follow-up question is to determine what causes the longer steering reaction times of inexperienced drivers. Considering the previous empirical work, cited above, on the effects of experience on hazard perception times, and on steering avoidance failures in collision situations, three partially related mechanisms could be suggested: (a) The experienced drivers were better at anticipating that the overtaking POV could generate a situation that could require steering; (b) after braking had been initiated, experienced drivers needed a shorter time to grasp that the decelerating POV still remained a hazard, for example due to previous experience of similar situations; (c) with experience, drivers had become more prone to and comfortable with the use of steering, or steering and braking, as their first response to a collision conflict, rather than braking only.

All three of these proposed mechanisms can, to some extent, be understood as experienced drivers having more *experience* and greater *expectancy* of steering collision avoidance. A formulation in terms of expectancy fits well with the findings by Green (2000), that typical brake reaction times range from 0.7 s for fully expected stimuli, up to about 1.5 s for surprise events, steering reactions being a few tenths of a second faster, overall. The long brake reaction times observed in the unexpected scenario of this study (2.0 s and 1.7 s for inexperienced and experienced drivers, respectively), thus seem to suggest that in both experience groups, the drivers were not at all expecting the POV to apply deceleration after overtaking. On the other hand, the average times between braking initiation and steering initiation (1.4 s and 0.8 s for inexperienced and experienced drivers, respectively), could be interpreted as the inexperienced drivers also being surprised that there was a need to apply steering in addition to braking, whereas the experienced drivers were not.

However, it should be pointed out that the very specific reaction time values proposed by Green (2000) have been criticized (Summala, 2000), and probably rightfully so.

4.2. Impact of ESC on avoidance

4.2.1. Unexpected avoidance

In addition to the clear division of the x axis, into colliding and non-colliding drivers, Figure 4 also suggests a division along the y axis: All three drivers applying a maximum steering wheel angle of about 100° or greater experienced full loss of yaw control, whereas the other drivers, who applied smaller evasive steering magnitudes, did not experience yaw control loss. Thus, as could be expected, yaw instability seems closely correlated with heavy steering.

In total, including the three drivers experiencing control loss, 9 drivers out of 48 (19%) applied ESC-relevant manoeuvring (i.e. manoeuvring such that an ESC intervention was triggered, or would have been triggered, had the ESC system been active). This is comparable to what was obtained by Dela et al. (2009), and suggests that simulator-based testing of truck ESC by means of unexpected scenarios remains problematic, in the sense that experiments may need to involve a large number of drivers in order for any effects of ESC to be measurable.

4.2.2. Repeated avoidance

Since the limitation just mentioned was anticipated, the instruction-based, repeated avoidance scenario test setting was also included in the study. In the repeated avoidance setting, the frequency of ESC-relevant manoeuvring was markedly higher (76%) and, here, results indicate that the ESC system did provide the type of benefits it is designed to provide: Reductions of skidding (in terms of maximum body slip angle; $r = 0.38$; Figure 8a), and of control loss frequency ($r = 0.45$; Figure 8b).

As mentioned in Section 1, one prior hypothesis was that driving experience could have an impact on the usefulness of ESC. The results provide some indications in the direction of experienced drivers having slightly less use of ESC, but inconclusively so: (a) the significant interaction in the unexpected avoidance data, between experience and ESC state, for large steering wheel reversals, could be interpreted as the experienced drivers needing to apply greater steering effort when ESC was present, whereas the opposite seemed to occur for inexperienced drivers. However, this interaction was *not* observed in the repeated avoidance data, despite the higher frequency of ESC interventions. (b) Comparing averages, the reductions of skidding and control loss due to ESC in the repeated scenario were smaller for experienced drivers. Furthermore, as mentioned in Subsection 3.2, when analysing the experience groups separately and non-parametrically, the reduction in skidding was statistically significant only for inexperienced drivers. However, the Pearson correlation coefficient still indicated a medium-sized effect for the experienced drivers ($r = 0.34$), so the lack of significance could to some extent be attributable to the reductions in test power associated with non-parametric testing and smaller sample sizes. Also, the reductions in control loss frequency were statistically significant for both experience groups separately. Overall, it is possible that these findings are caused by the experienced drivers' control behaviour being less in line with the ESC system's model of driver intentions, something which could be due either to some highly developed driver control strategies, but just as well to a tendency of applying excessive countersteering during skidding. Further analysis of these matters is needed, but is beyond the scope of this paper.

4.2.3. Comparing unexpected and repeated avoidance

Given the seemingly higher face validity of the unexpected scenario, due to its higher degree of realism, it is relevant to try to understand why this scenario did not generate observations of ESC benefits, whereas the repeated scenario did. The limited size of the sample of ESC-relevant unexpected avoidance manoeuvring may be hypothesized to be one contributing factor (such that increasing the experiment size could, in theory, lead to observations of ESC benefits also for the unexpected scenario), but whether or not this really is the case cannot be concluded from the data and analyses presented here.

Another possible factor to consider is that the repeated avoidance scenario seems to have been more successful at placing drivers in situations with a real risk of loss of yaw control. There were no statistically

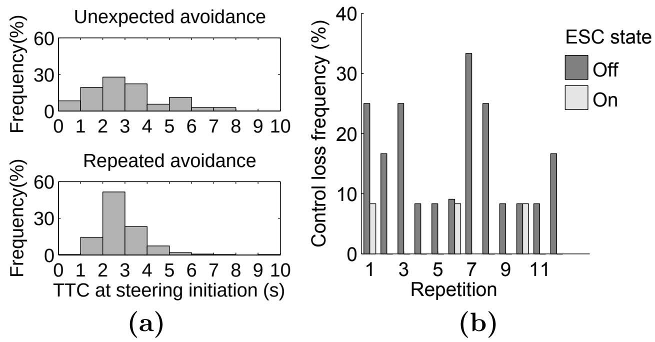


Figure 12: *(a) Distributions of TTC at steering initiation, for the unexpected and repeated avoidance scenarios. (b) Frequency of control loss in the repeated avoidance scenario, per repetition and ESC state.*

significant differences between the unexpected and repeated scenarios on the generated steering avoidance situations (in terms of speed and TTC at steering initiation; Figures 9c and d). However, a closer look at the data, such as in Figure 12a, indicates that the steering avoidance situations in the repeated scenario were a narrowed-down subset of the steering avoidance situations occurring in the unexpected scenario. Specifically, Figure 12a and, to some extent, also Figure 3 suggest that the repeated scenario eliminated the latest and earliest of the unexpected steering attempts, and instead had drivers more frequently initiating steering from around a TTC of two to three seconds. According to Figure 4, this was a type of situation from which collision could be avoided, but not without risk of losing yaw control, something that could explain the higher frequency of ESC-relevant manoeuvring in the repeated avoidance scenario, in turn yielding a larger effective sample for the study of ESC effects.

The above argument could be taken to imply that, if the experiment size were increased, the ESC benefits observed for the repeated avoidance in the present study should be guaranteed to appear also in the unexpected scenario, for unexpected steering attempts starting from a TTC of two to three seconds. However, for this to be the case, it would also be required that driver control behaviour *after* initiation of steering from a given steering avoidance situation, be the same in unexpected and repeated avoidance, something that cannot be conclusively stated based on the analyses presented here. On the contrary, as touched upon above in this paper, Hollnagel and Woods (2005) suggested that differences in the expectancy for, and previous experience of, a control task could lead to qualitatively different *control modes* being employed. If so, it seems possible that transitions between control modes could occur in the transition between unexpected and repeated collision avoidance. Further analysis or discussion of these aspects fall outside the scope of this paper.

A completely different type of explanation for why ESC benefits were only observed in the repeated scenario could be that drivers had to *learn* how to drive with the system, before being able to enjoy its benefits. The idea behind ESC is clearly not that any such learning and adaptation should be needed, and previous research can be taken to suggest that ESC reduces control loss even for drivers who are not aware of the system's presence in their vehicle (Høye, 2011). Nevertheless, the possibility deserves brief attention: If learning effects were the cause of ESC benefits in the repeated avoidance scenario, this should have been observable as improvements over repetitions in situation outcome measures, and more markedly for repetitions with ESC activated. However, no interaction effects of that kind were observed. Figure 12b shows the frequency of control loss as a function of repetition and ESC state and, if anything, it suggests that repetition led to improvements for driving *without* ESC, in other words the opposite of what this hypothesis would predict[7].

[7] Note that repetitions 1 and 7, at which peaks of control loss frequency for ESC off are discernible in Figure 12b, correspond

4.3. Methodological aspects

4.3.1. Appending a critical scenario to another experiment

The specific observed differences between unexpected avoidance occurring at the beginning of the ESC experiment, as compared to at the end of the LKA experiment (Figure 7), could be interpreted in terms of prior experience of the winter environment in which the unexpected scenario took place. The ESC experiment drivers had driven for ten minutes in this winter environment, including five decelerations to full stop (during which road friction was still good), before starting the four-minute drive that ended with the unexpected scenario. The LKA drivers, on the other hand, were moved directly to this four-minute drive from a thirty-minute experiment in summer surroundings. It could be hypothesised that this may have generated, among LKA experiment drivers, a heightened expectancy for difficult traffic situations in general, and for low-friction road conditions in particular. Such an interpretation seems to be supported by the observations of more careful brake application (Figure 7a), as well as an earlier steering avoidance, measured as shorter steering reaction times (Figure 6c; a difference which was not statistically significant) and as higher minimum TTCs (Figure 7b; significant). The lower severity ratings provided by LKA drivers (Figure 7c) could be understood as resulting from the higher minimum TTCs.

As mentioned in Subsection 3.1, the analyses of effects of experience on reaction times and collision outcome were carried out on the full data set of recordings from both experiments, since for these dependent variables there were no significant effects of experiment (nor any interactions between experiment and experience). Furthermore, a closer look at Figure 6c indicates that the lower steering reaction times in the LKA experiment were due mainly to the experienced drivers, and the data for minimum TTC exhibit a similar pattern. This observation could be interpreted as the experienced drivers of the LKA experiment being more sensitised than the low-experience LKA drivers, by the above-mentioned change from summer to winter environment. In other words, the observed differences in driver behaviour between the two experiments can be nicely integrated with the explanatory model sketched in Subsection 4.1.3 above, as the experienced LKA drivers being able to add also the change of environment to the set of circumstances on which they based their higher expectancy for a possible need of steering avoidance manoeuvring.

4.3.2. Repeated, instruction-based collision avoidance

The differences between repeated and unexpected scenarios in terms of braking (Figures 9a and b), and to some extent also the effects on braking of repetition itself (Figures 10a and b) suggest, as expected, that the adopted paradigm for repeated avoidance is not suitable for the study of braking behaviour. However, as discussed above, for the purposes of this study it proved useful, by frequently generating a type of steering avoidance situation highly relevant to the evaluation of ESC. Furthermore, the other observed effects of repetition (Figures 10c and d) did not seem to have any major impact on this evaluation.

As has been discussed above, this type of repeated avoidance testing has lower face validity than testing with unexpected scenarios. However, it could be argued that the validity is higher than for methods involving predefined control inputs or tracks to follow (such as described in Section 1), precisely since here, drivers are free to adopt whichever escape paths and control strategies they prefer, something that arguably could make behaviour more similar to behaviour in real traffic.

One final aspect to be noted is that, compared to an unexpected scenario, the repeated avoidance paradigm alters the distribution of responses to the rear-end situation, yielding more frequent steering responses (here, 99% versus 77%), and a more narrow distribution of steering response times (see Figure 12a). Therefore, care will need to be taken in any comparison of ESC benefit figures, such as control loss reduction ratios, from this type of paradigm with figures from studies based on unexpected avoidance paradigms or on accident statistics.

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to the subjects' very first repetitions without ESC, since half of the drivers began the experiment with ESC off, and the rest had ESC turned off before repetition 7.

5. Conclusions

In the unexpected lead vehicle braking scenario of this study, the most striking effect of experience was that inexperienced drivers collided considerably more often than experienced drivers, and in general, the results suggest that this was caused mainly by inexperienced drivers having longer reaction times to steering initiation. Furthermore, the obtained data seem to provide some support for the hypothesis that these differences in steering reaction times could be due to experienced drivers having a greater expectancy for steering avoidance in this type of situation.

The range of behavioural responses observed in the unexpected scenario was wide, and the type of yaw instabilities targeted by the ESC yaw control system occurred only for a small subset of behaviours. The consequent limitation in effective sample size could be one reason for the lack of effects of ESC in the unexpected avoidance data.

However, the instruction-based paradigm for repeated avoidance was able to frequently reproduce the type of steering avoidance situations for which losses of yaw control were observed in the unexpected scenario. In repeated steering avoidance starting from this, less variable, range of initial conditions, statistically significant benefits of ESC were observed, in terms of reductions of skidding and control loss. These benefits did not seem to be attributable to learning effects. There were some indications of experienced drivers gaining slightly smaller benefits from the system, but the reductions of control loss were statistically significant for both experience groups separately. In summary, it seems that the ESC system reliably improved the stability of the drivers' repeated avoidance manoeuvring. However, given the possibility of subtle differences in driver control behaviour between unexpected and repeated collision avoidance, the present analyses do not allow any precise predictions of the extent to which these repeated-avoidance benefits of ESC could be present also in unexpected avoidance.

In addition to the repeated avoidance approach to increase sample sizes, the approach of appending one critical situation to the very end of another simulator experiment was evaluated, and in this specific study it was found useful. However, the obtained results also highlight that whenever systematic variations are introduced in what drivers experience in the simulator prior to a situation under study, it is recommendable to carefully control for any effects of these variations on the drivers' behavioural responses.

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Paper II

Driver behaviour in unexpected critical events and in repeated exposures - a comparison

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ORIGINAL PAPER

Driver behaviour in unexpected critical events and in repeated exposures – a comparison

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Abstract
Purpose This paper aims to determine how truck driver steering behaviour seen in repeated exposures to a critical event correlates to the behaviour resulting from an unexpected exposure to the same event.
Methods Test subjects were exposed to an unexpected critical event in a high-fidelity driving simulator. Next, a slightly modified version of the scenario was repeated several times for each subject. The driver behaviour was then analysed using standard statistical tests.
Results It was found that, in general, drivers keep most of their steering behaviour characteristics between test settings (unexpected and repeated). This is particularly interesting since a similar kind of behaviour preservation is generally not found in the case of *braking* behaviour. In fact, only one significant difference was found between the two test settings, namely regarding time-to-collision at steering initiation.
Conclusions In experiments involving both an unexpected event and several repeated events one can, at least in some cases, design the repeated event such that behavioural data collected from that setting can be used along with data from the unexpected setting. Using this procedure, one can significantly increase the amount of collected data, something that can strongly benefit, for example, driver modelling.

Keywords Driver behaviour · Repeated exposures · Evasive steering · Driving simulator · Driver modelling

1 Introduction

Road traffic accidents constitute a large problem on a global scale. Apart from great economical and social costs, the accidents also cause a significant number of injuries and deaths. The number of worldwide fatalities have recently been estimated at over one million per year [15], of which 8 % occur in Europe. Driver behaviour is widely considered as a contributing factor in many road traffic accidents. Therefore, research efforts regarding the safety aspects of such behaviour have been intensified during recent years [9].

As a way to understand and further study the impacts of driver behaviour, models that capture aspects of driver behaviour are being developed (for a recent review, see [12]). An important goal of driver behaviour research is to find simple phenomenological relations that explain driver behaviour in certain situations. Examples of such behaviour could, for instance, be braking behaviour as a function of headway to an obstacle [8], or steering behaviour as a function of perceptual inputs [14].

Data used in the development of a driver model are typically collected from real-world driving experiments or driving simulator studies. In most experimental arrangements, the intention is to mimic realistic scenarios in order to measure realistic behavioural responses in drivers. However, fully realistic scenarios cannot easily be accomplished

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in a non-naturalistic driving experiment. In particular, in order to obtain sufficient amounts of data for statistical analysis and development of driver models, it might be necessary to expose each driver to the studied scenario multiple times. This is so since, for economical and other reasons, one often cannot involve a very large number of drivers in an experiment. Furthermore, for driver model development, in view of the individual differences between drivers, one generally needs quite many data points from each driver in order for meaningful model development to be possible. Before making use of the results obtained from such experiments one must therefore first understand the effects (if any) of repeated exposures to the scenario under study.

Previously, several studies have considered driver reaction times in braking scenarios [5]. It has been shown that, when reacting to expected (e.g. repeated) events, drivers' brake reaction times are reduced significantly [2, 10]. Furthermore, it has been concluded that test subjects brake earlier and more strongly in repeated events [10]. However, it has also been shown that some behavioural aspects might be preserved in repeated exposures [2]. In this paper, the effects on driver *steering* behaviour caused by repetition of a critical event are studied.

The data used for the analysis presented in this paper were collected in a truck simulator study regarding driver behaviour in connection with an *electronic stability control* (ESC) system. In the experiment, the truck drivers were asked to drive on a road in a winter environment, where they were exposed to an unexpected critical lead vehicle braking scenario, inducing a rapid steering manoeuvre. In a brief pre-study, the unexpected scenario was not found to be reliable in inducing sufficient ESC-relevant (loss of control) data, and the scenario was therefore repeated several times for each driver.

The analysis presented here will be centred on the effects of steering behaviour caused by the repeated exposures to the scenario rather than the effects on driver behaviour caused by the ESC system. Furthermore, only events in which the driver successfully evaded a collision with the lead vehicle will be considered. Events involving a collision should be studied separately since the typical driver behaviour appears to be fundamentally different, in particular for the unexpected case.

In order to ascertain the validity of steering data collected from repeated exposures, a statistical comparison between aspects of the unexpected and the repeated data has been carried out. Four different criteria (C1-C4) for measuring the validity of repeated exposure data have been defined as:

- C1 *Scenario tuning*: Can the repeated scenario be tuned so that the steering manoeuvre is initiated under similar conditions in both test settings (unexpected and repeated)? If so, when the truck driver initiates the evasive steering, there are no crucial differences in road position, speed, or headway to the lead vehicle, regardless of the test setting (unexpected or repeated).
- C2 *Manoeuvre similarity*: Is the steering manoeuvre carried out in a similar fashion in both settings, that is without crucial differences in maximum steering wheel angles, steering wheel rates, or steering wheel reversal rates?[1]
- C3 *Preservation of individual behaviour*: Do the test subjects keep their individual steering behaviour characteristics between the two test settings?
- C4 *Effects of learning*: Are there no crucial effects of learning on how steering avoidance is carried out, meaning that test subjects do not change their steering performance over repetitions?

2 Method

Data were collected in a high-fidelity moving-base truck simulator at the Swedish National Road and Transport Research Institute (VTI). The simulator uses a moving base platform providing lateral movement as well as roll and pitch rotations. A visual system provides a 105° field of view using forward-facing projectors, and emulated rear mirrors using monitor screens. For the study considered in this paper, a six-wheeled rigid truck with a wheel base of 6.2 m (from first to last axle) was simulated.

2.1 Simulator experiment

2.1.1 Scenario

The main scenario used in the experiment was originally proposed in [2] and involves a critical lead vehicle braking scenario, as illustrated in Fig. 1. The scenario took place on a divided four-lane motorway with two lanes in each direction. The road speed limit for trucks was 80 km/h. While the test subject was driving at speed v_1 in the right lane, a passenger car, referred to as the *principal other vehicle* (POV), overtook the truck at speed $v_2 = R_x v_1$ using the left lane, where $R_x > 1$ is a constant. At a time headway T_{cut} with respect to the truck, the POV (at *lateral* speed v_{cut}) changed from the left to the right lane. Once in the right lane, the POV continued forward, still at speed v_2. Then, without any apparent reason, at time headway T_b, the POV braked strongly with the constant deceleration d_b. The deceleration continued until the POV stopped completely (with one exception, described in the next paragraph). Right before the deceleration, the speed was instantaneously set to v_1 in

[1] Steering wheel reversal rates are explained in Section 2.2.2.

order to ensure that the time headway was always less than, or equal to, T_b. When the critical scenario was initiated, the road friction was lowered from μ_1 to μ_2 in order to emulate a slippery road surface.

As seen in Table 1, the scenario was parametrized for three different versions: (i) *unexpected avoidance* (UA), (ii) *repeated avoidance* (RA), and (iii) *catch trial* (CT), i.e. a version in which no steering avoidance was needed. In the CT, the POV deceleration ended at speed v_3 and was then followed by an acceleration a_{acc}. The CT was included so that the drivers would not be certain regarding the nature of a repeated event, i.e whether it was an RA scenario or a CT scenario.

The parameters for the RA scenario were chosen so that the test subjects would initiate their steering approximately at the same time in the repeated events as they did in the unexpected scenario. In order to meet this requirement, a larger deceleration d_b was used in the repeated events and in the catch trials so as to compensate for reduced reaction times [5], and the speed v_3 was used so as to control the time at which the test subjects initiated evasive steering. Appropriate parameter values were chosen based on results from

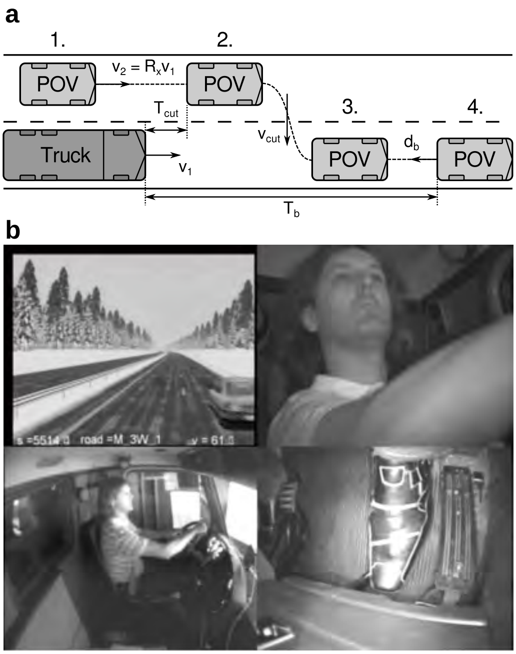

Fig. 1 Top panel: The critical lead vehicle braking scenario where a passenger car overtakes the test subject's truck. The numbers 1-4 denote different points in time. Bottom panel: A snapshot from the experiment. Here, one of the test subjects is in the process of avoiding the POV in the unexpected avoidance scenario

Table 1 Parameters for the critical lead vehicle braking scenario

Parameter	UA	RA	CT
R_x	1.15	1.15	1.15
T_{cut}	0.9 s	0.9 s	0.9 s
v_{cut}	5.4 km/h	5.4 km/h	5.4 km/h
T_b	1.5 s	1.5 s	1.5 s
d_b	0.35g	0.45g	0.45g
μ_1	0.7	0.7	0.7
μ_2	0.25	0.25	0.25
v_3	–	–	45 km/h
a_{acc}	–	–	0.3g

UA, RA, and CT refer to *unexpected avoidance*, *repeated avoidance*, and *catch trial* versions of the scenario, respectively. See the main text for the parameter definitions

(i) a brief pre-study in a fixed base simulator, and (ii) computer simulations using a simple driver model. Both the UA and RA events were tuned such that evasive braking alone was insufficient to avoid a collision.

2.1.2 Experimental procedure

The experiment consisted of three parts with a preceding training session. The last part, involving a double lane change on a cone track, will not be discussed in this paper. The training session, inspired by [7] and [13], included driving in steady-state traffic as well as a few repetitions of non-critical braking and steering exercises. The total length of the training session was about ten minutes and it was carried out on the same simulated road as the critical scenario (described above).

In the first part of the experiment, the test subjects were instructed to drive normally at 80 km/h on the motorway described above. After approximately four minutes of driving, including four overtaking vehicles and a non-critical double lane change induced by a road construction site, the UA scenario occurred. Unknown to the test subjects, half of them had the ESC system present in their trucks, and half did not.

In the second part of the experiment, the subjects were informed about the ESC system and whether or not it was present in their vehicle (explained as an "anti-skid system"). They were also instructed about the RA and CT scenarios (described above), and that both scenarios would be repeated several times in a random order. The drivers were then asked to drive at 80 km/h on the same motorway as in the previous part, and to apply evasive steering only when they considered it required in order to avoid a collision (i.e. only in the RA event).

During the second part, each subject experienced, in random order, four overtaking vehicles, six occurrences of the

RA scenario, and eight occurrences of the CT scenario. Note that, in no case did the CT scenario evoke a critical steering avoidance behaviour, and the analysis below thus concerns only the RA scenario in relation to the UA scenario.

2.1.3 Test subjects

In total, 24 test subjects participated in the experiment. The drivers were divided into two equally large groups based on driving experience (*low* or *high*). The drivers belonging to the low-experience group were mainly recruited from a local driving school, where they soon would get their licence for truck-trailer combinations. However, all low-experience drivers already had a driver's licence for the rigid truck simulated in the experiment. The drivers belonging to the high-experience group were mainly recruited from local hauler companies.

2.2 Experimental design

The steering manoeuvre was divided into four time intervals, as illustrated in Fig. 2. The first interval, I_1, starts at time t_0 when the overtaking car initiates braking, and ends at time t_1 when the truck driver initiates evasive braking. The second interval, I_2, starts at time t_1, and ends at time t_2 when the truck driver initiates evasive steering. The interval I_3 starts at time t_2, and ends at time t_3 when the truck driver has reached the maximum steering wheel angle to the left. Finally, the interval I_4 starts at time t_3, and ends at time t_4 when the truck driver reaches the largest steering wheel angle to the right. Time t_4 is given as the first (in time) local minimum at which the steering wheel angle signal reached a value less than -20°, time t_3 is given as the time of the largest steering wheel angle between t_0 and t_4, and time t_2 is given as the time of the first steering wheel angle value below 8° when tracking the signal *backwards* from t_3. Note that, for the schematic illustration in Fig. 2, t_4 could have

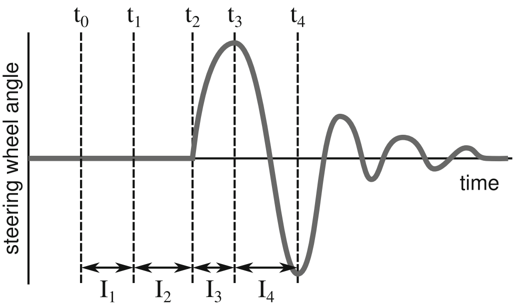

Fig. 2 A schematic illustration of a steering manoeuvre required to avoid a collision in the lead vehicle braking scenario. The overtaking vehicle starts to brake at time t_0, and the truck driver initiates braking at time t_1

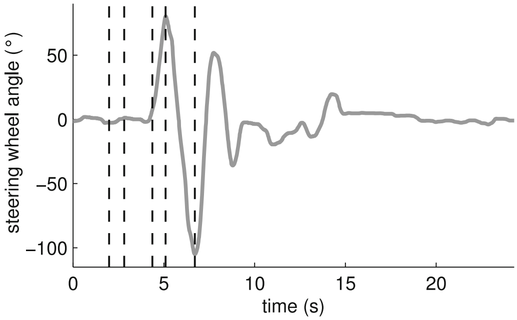

Fig. 3 A typical steering signal extracted from actual driving data. The vertical lines denote the time intervals described in Fig. 2

be defined as the global minimum of the steering wheel angle. However, some steering manoeuvres involved a control loss, in which case subsequent minima of the steering wheel angle could be deeper than the first minimum, hence the definition of t_4 given above. An actual steering response is presented in Fig. 3.

2.2.1 Independent variables

The independent variables considered in this paper are: *test setting* (UA or RA), and *repetition* (one through six).

2.2.2 Dependent variables

A number of dependent variables, presented in Table 2, were extracted from each event in the driving data. *Time to collision* (TTC) is measured as the time it would take for the truck to cover the distance between the front of the truck and the rear of the POV (assuming current POV and truck speeds, i.e. disregarding any accelerations). The *steering wheel reversal rate* (SWRR), was defined as the number of steering wheel reversals per minute, larger than a certain minimum angular value [11].

Table 2 The different measures analysed

Measure	Source	Criteria	Normal
TTC	t_2	C1, C3, C4	Yes
lateral position	t_2	C1, C3, C4	No
longitudinal speed	t_2	C1, C3, C4	Yes
steering wheel angle	t_3, t_4	C2, C3, C4	No, No
steering wheel rate	I_3, I_4	C2, C3, C4	No, No
SWRR (5°)	I_3, I_4	C2, C3, C4	No, Yes

The data sources are presented in Fig. 2. The list of criteria is presented at the end of Section 1. Normality was tested for each variable using the Shapiro-Wilk test

2.2.3 Statistical tests

Two types of tests were used when testing for significant differences in dependent variables between test settings (i.e. criteria C1 and C2). If the samples of a dependent variable were found to be normally distributed a *dependent t-test for paired samples* was used, otherwise a *Wilcoxon signed-rank test* was used. Normality was tested using the *Shapiro-Wilk* test, as reported in Table 2. For each test subject and dependent variable, the unexpected event as well as the mean of all repeated events are used as one pair of values. Furthermore, for each significance test, the *Pearson's correlation coefficient r* was calculated as a measure of *effect size*. The use of the paired samples t-test or the Wilcoxon test implies that no assumption regarding the homogeneity of variances needs to be made [4].

Pearson's correlation coefficient is also used for two other purposes, first to determine the paired sample correlation of a dependent variable between test settings, in order to see whether driver behaviour is transferred between settings (C3) and second to determine the correlation of a dependent variable between repetitions, in order to study learning effects (C4).

Three of the four criteria involve an absence of a crucial difference in behaviour. Here, a crucial difference is defined as a *medium effect size* ($|r| > 0.3$) [1].

3 Results

According to the experimental set-up, the maximum amount of data was 24 repetitions of the unexpected event, and 144 repetitions of the repeated event. Data from one of the repeated events were lost due to experimental problems. In eight unexpected and two repeated events, the test subjects did not attempt any evasive steering at all. A successful evasive manoeuvre (i.e. without collision) occurred in 9 of the unexpected events and 88 of the repeated events. As stated in the end of Section 1, all events where a collision occurred were discarded. Four other repeated events were discarded since the test subject violated the instructions by initiating steering directly when the POV began braking. Finally, data from one unexpected event were discarded since the driver steered much earlier compared to the other test subjects (with a TTC of 7.9 s). In Table 3, *Repeated A* refers to all repetitions matching the corresponding row criterion, while *Repeated B* only includes matching repetitions that also share a test subject represented in the left column. In Table 4, the 33 filtered data points in *Repeated B* are matched to their corresponding test subject. Figure 4 summarizes the TTC at steering initiation for the retained data points after filtering.

Table 3 The top row shows the theoretical upper limit on the amount of data, based on the experimental design, whereas the second row shows the actual amount of data collected

	Unexpected	Repeated A	Repeated B
Design	24	144	144
Acquired	24	143	143
Steering	16	141	94
No collision	9	88	36
Filtered	8	84	33

The third row shows the number of events in which the driver initiated steering (i.e. applied a steering wheel angle above 15°), the fourth row shows the number of events where the driver successfully avoided a collision, and the bottom row shows the amount of data after filtering (see the main text for a description). The middle column includes repetitions from all drivers whereas the right column only includes repetitions collected from drivers represented in the left column

Table 4 The number of repetitions used for each of the test subjects presented in the last row of the last column of Table 3

Test subject	1	2	3	4	5	6	7	8
Repetitions	3	5	3	5	6	5	3	3

For each test subject, the means of the variables extracted from corresponding repetitions are used in the t-tests

In the rest of this section, the steering manoeuvre will be analysed by comparing the dependent variable *pairs* extracted from the unexpected events with the variables from the repeated events. In order to make it possible to use a paired sample t-test, all repeated events from the same test subjects were merged by calculating the mean of each dependent variable. Therefore, 2×8 values will be compared in each t-test.

In Figs. 5, 6, 7, 8 and 9, the left panel compares the unexpected and averaged repeated scenarios, whereas the right panel compares the repetitions over repetition number. The left panel includes the eight sample pairs used in the t-tests,

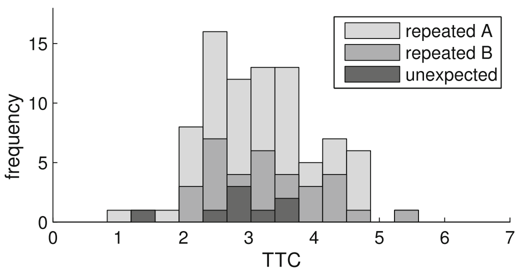

Fig. 4 The TTC at steering initiation of all unexpected and repeated events remaining after filtering (see Table 3)

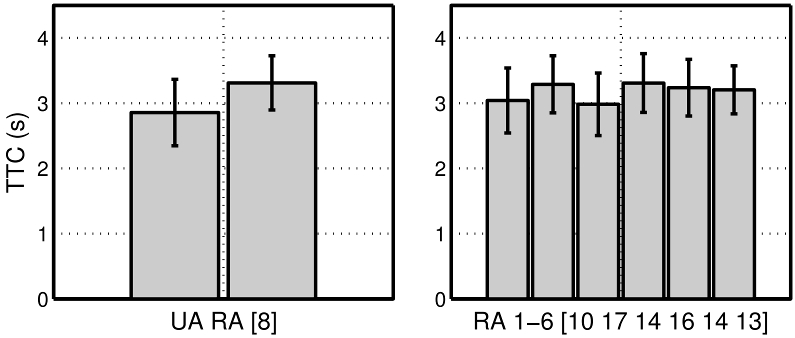

Fig. 5 The TTC at time t_2 (steering initiation)

and the right panel includes the 84 repetitions presented in the middle column of Table 3. Error bars show 95 % confidence intervals, calculated under the assumption of a normal sampling distribution.

3.1 Situation at steering initiation

When analysing the situation at steering initiation (t_2) between test settings, a significant difference was found in one out of three dependent variables: By using the t-test, the significant difference was found in TTC (see Fig. 5) between UA ($M = 2.86$, $SD = 0.74$) and RA ($M = 3.31$, $SD = 0.60$); $t(7) = -2.4$, $p < 0.05$, $r = 0.67$. No significant difference was found in lateral position (see Fig. 6) or longitudinal speed.

3.2 Steering manoeuvre

The steering manoeuvre was analysed by comparing six of the presented (see Table 2) dependent variables between the UA and the RA. The six variables include: (i) maximum steering wheel angle to the left (t_3), (ii) maximum steering wheel angle to the right (t_4), (iii) maximum steering wheel rate while turning left (I_3), (iv) maximum steering wheel rate while turning right (I_4), (v) SWRR (5°) while turning left (I_3), and (vi) SWRR (5°) while turning right (I_4). No significant differences were found between the two test settings (UA and RA) for any of the variables. However, one of the variables, namely steering wheel rate in the interval I_4 (see Fig. 8) gave a considerably larger effect size ($p > 0.05$, $r = -0.59$) compared to the other five variables ($p > 0.05$, $|r| \leq 0.30$). Two of the other variables, steering wheel angle at time t_4 ($p > 0.05$, $r = -0.25$) and SWRR (5°) in the interval I_3 ($p > 0.05$, $r = -0.30$), are exemplified in Figs. 7 and 9 respectively.

3.3 Preservation of steering behaviour

By calculating a *paired sample correlation*, using the same 2×8 values as above, one can study the preservation of steering behaviour between both test settings. When testing all the nine dependent variables listed in Table 2, it was

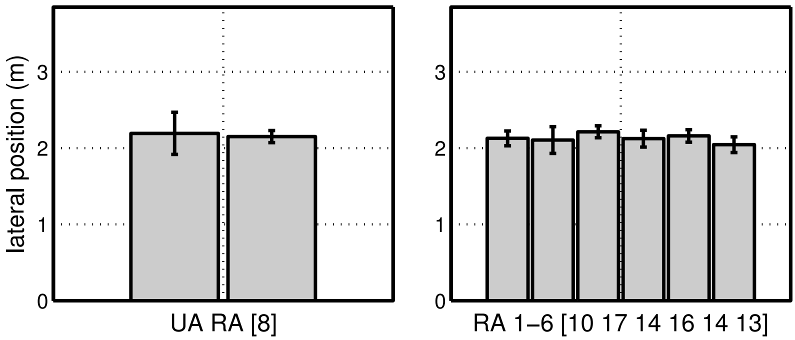

Fig. 6 The lateral position at time t_2 (steering initiation)

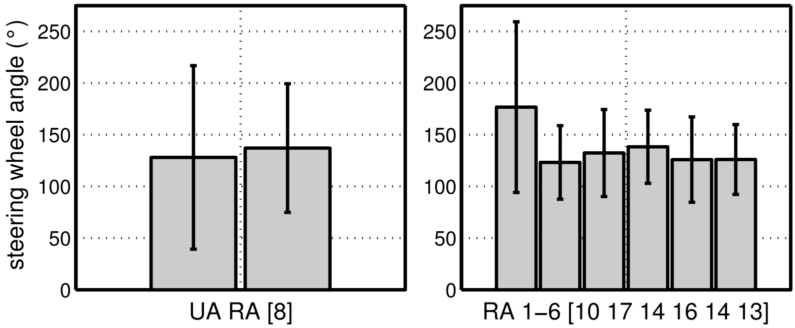

Fig. 7 The steering wheel angle at time t_4 (maximum steering wheel angle to the right)

found that four of them had a significant correlation, namely steering wheel angle at times t_3 ($p < 0.05$, $r = 0.94$) and t_4 ($p < 0.05$, $r = 0.95$), and steering wheel rate in the intervals I_3 ($p < 0.05$, $r = 0.93$) and I_4 ($p < 0.05$, $r = 0.97$). No other variable correlation showed significance, nor any high values of the Pearson's correlation coefficient r. In Fig. 10, two examples of paired sample correlation are presented, one with a large r value, and one with a small r value.

3.4 Learning effects in steering behaviour

For the analysis of potential learning effects, the data collected in the unexpected scenario were not used. Therefore, since the use of paired data was not required, the 84 data points presented in the middle column of Table 3 could be used. In this case, a strict test of significance would be complicated (but not impossible) since each driver is only represented in a subset of the repetitions, with different subsets for different drivers. Therefore, only the Pearson's correlation coefficient was determined for each dependent variable, and for which a large (absolute) r value would indicate a learning effect.

By calculating Pearson's correlation coefficient for each dependent variable, it was found that no large absolute r values existed. For three of the values, the modulus exceeded 0.1, namely SWRRs in the intervals I_3 ($r = -0.12$; see Fig. 9) and I_4 ($r = 0.19$), and steering wheel angle at time t_4 ($r = 0.11$; see Fig. 7).

4 Discussion

The discussion is structured as follows: First the findings in Section 3 will be related to the criteria listed at the end of Section 1. Then, aspects of the experimental set-up will be discussed, focusing on repeated critical events for collecting steering behaviour data. Finally, the general applicability of such data will be discussed in the context of driver modelling.

4.1 Criteria

The validity of the first criterion (C1) regarding *scenario tuning*, cannot be entirely confirmed: When drivers initiated evasive steering, (at time t_2), there was a significant

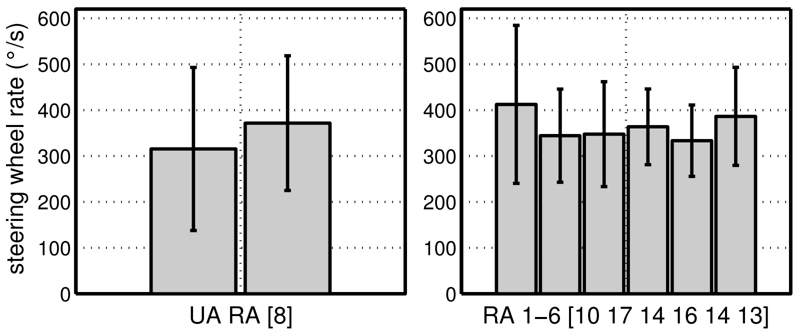

Fig. 8 The maximum steering wheel rate in interval I_4 (between maximum steering wheel angle to the left, and maximum steering wheel angle to the right)

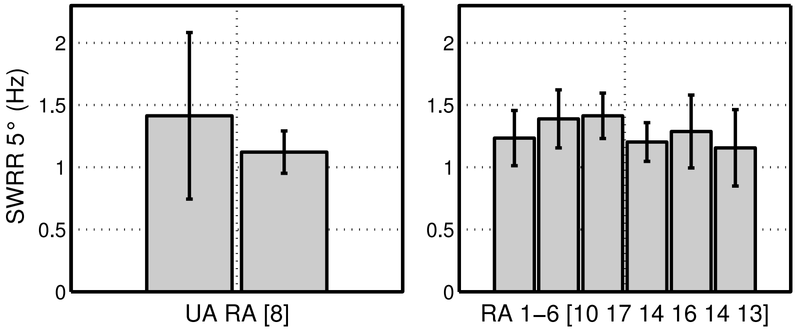

Fig. 9 The 5° SWRR in interval I_3 (between steering initiation, and maximum steering wheel angle to the left)

difference in TTC ($p < 0.05$, $r = 0.67$), such that initiation occurred, on average, 0.5 s earlier in the repeated events, resulting in a slightly less critical situation. However, even though the difference is significant and with a large effect size, it might be argued that the difference is *sufficiently low* for C1 to be fulfilled, since drivers appear to behave similarly during the remainder of the UA and RA scenarios (as discussed below).

At the time of steering initiation, there was no significant difference in lateral position or speed between test settings. For lateral position, one could intuitively assume that test subjects would position their trucks further to the left in a repeated event. No such tendencies were seen, however.

The validity of criterion C2, regarding *manoeuvre similarity*, can be confirmed, as there were no significant differences between any analysed steering wheel angles, steering wheel rates, or SWRRs. There is, however, an apparent difference (not significant) regarding steering wheel angle at time t_4 (see Fig. 7) in the very first repetition. The same phenomenon can be seen in the steering wheel rate during the interval I_4 (see Fig. 8). A possible explanation could be that test subjects overestimate the severity of the situation in the first repetition, and then regain a behaviour similar to the one seen in the unexpected event.

Also criterion C3, regarding *preservation of individual behaviour* appears to be valid. Using paired sample correlation, it was shown that test subjects keep their steering characteristics very well (r values close to 1) regarding maximum steering wheel angles and steering wheel rates. They do not, however, preserve their characteristics regarding SWRRs. Arguably, the criterion can still be considered to be valid, since SWRRs are less important compared to maximum steering wheel angles and steering wheel rates when considering the outcome of the steering behaviour, i.e. avoiding the collision. It should also be pointed out that there were, as stated for the previous criterion, no significant differences in SWRRs between test settings on the *population* level.

Interestingly, from Fig. 10 one can see that drivers tend to have a lower SWRR value (1 Hz) in the repeated events compared to the unexpected events. A possible explanation, if one considers experience to be scenario-specific, could be related to the fact that inexperienced drivers (in this case meaning drivers that have not yet been exposed to the critical event) in general have a larger SWRR compared to

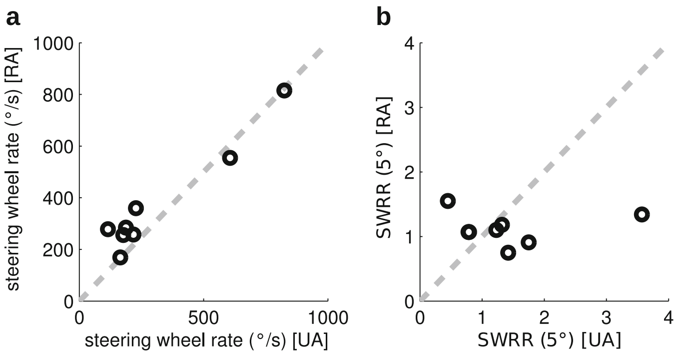

Fig. 10 The correlation of two different dependent variables, namely steering wheel rate in the interval I_4, and SWRR (5°) in the interval I_3. The first had the largest Pearson's correlation coefficient ($r = 0.97$) of all dependent variables, and the second had the smallest coefficient ($r = 0.03$)

those drivers who have experienced the critical event [3]. In order to explain the observed phenomenon in terms of control, one can hypothesize that an experienced (in the scenario) driver carries out the steering manoeuvre in an open-loop manner, rather than in a closed-loop manner [6]. However, as mentioned above, even though a difference in SWRR between test settings seems probable, no statistically significant difference was found.

Finally, the validity of criterion C4, regarding (the absence of) *learning effects* can be confirmed: There were no crucial ($r > 0.3$) effects of learning for any of the dependent variables. There were some small effects of learning for the SWRRs ($r = -0.12$, see Fig. 9, and $r = 0.19$), and the maximum steering wheel angle to the right ($r = 0.11$). However, such small effects would hardly have any bearing here, considering the small number of repetitions.

It should also be pointed out that there were *no* large effects of learning on lateral position ($r = -0.07$). Again, one would intuitively assume that drivers should tend to gradually keep further to the left over repetitions. However, no such behaviour was seen.

4.2 Experimental set-up

In general, and especially when considering critical situations, the amount of available data is limited. Furthermore, when collecting data from critical situations, there are problems involving safety, cost, and test subject expectancy.

By using multiple repetitions of a critical event, the number of acquired data points can be strongly increased. Furthermore, by using repeated events, one can reduce costs by decreasing the total number of test subjects as well as increasing the efficiency (event rate) during the experiment. Safety problems can also be addressed by using repetitions since it allows for test subjects to be well instructed during the experiment.

However, repetitions typically require some additional work. First, the repeated scenario must be designed to compensate for known effects on driver behaviour. For instance, it was concluded in [10] that driver braking behaviour is largely affected by repetitions, in particular by decreased reaction times and stronger braking. In the case considered here, a significant difference between test settings was found in the TTC at steering initiation. In retrospect, this difference could perhaps have been eliminated by further tuning the parameters for the RA scenario. Secondly, the data collected from repeated scenarios must be validated for the application at hand. For this purpose, it is highly recommended first to collect data from an unexpected version of the scenario under study, as was done in the experiment considered here, and then to make a comparative analysis between the data collected in the unexpected scenario and the repeated tests. Another reason for including unexpected events is that the behaviour observed in repeated events is probably only a subset of all possible types of behaviour for the given scenario.

4.3 Applicability in driver modelling

Since all four criteria (C1-C4) were found to be valid, possibly with the partial exception of C1, it has been shown that the steering behaviour collected in repeated events can be used in driver modelling, at least for the case of successful evasive manoeuvres. As seen in Table 3, only data from 8 out of 24 drivers were used in the comparison. From the remaining 16 drivers: (i) eight did not attempt steering at all, (ii) seven applied steering but still collided with the POV, and (iii) one steered much earlier compared to the other drivers. By using the data analysed in this paper, one can thus only cover a third of the observed behaviour. All four types of behaviour must be covered when generating a general driver model for the critical scenario under study. However, it should be pointed out that it is likely to be much easier to model those drivers that do not apply any evasive steering (i.e. another third of the drivers considered in this experiment).

5 Conclusion

In this paper, it has been shown that the steering behaviour observed in repeated critical scenarios to a large extent preserves the characteristics of the steering behaviour found in an unexpected critical scenario, making it possible to use data from repeated scenarios in, for example, driver modelling for evasive steering.

It has been demonstrated that a repeated scenario can be tuned so that evasive steering is initiated under the same conditions as in an unexpected scenario. Furthermore, it was found that there were no significant differences in lateral position and speed between test settings. There was, however, a significant difference in TTC ($p < 0.05$, $r = 0.67$), but it was argued that the difference did not seem to change the rest of the observed steering behaviour. No significant differences were found in the maximum steering wheel angles or the steering wheel rates during the manoeuvre itself.

It was also found that test subjects keep their steering characteristics between test settings. Very high correlation values (r close to 1) were obtained from paired sample correlation tests of maximum steering wheel angles and maximum steering wheel rates. Furthermore, no large effects of learning (measured using Pearson's correlation coefficient) were found in the collision avoidance manoeuvre.

Using repeated events in an experiment is recommended when large amounts of data are needed, for example when developing driver models. However, it is also recommended to combine the repeated events with an unexpected event in order to make it possible to validate the data collected in the repeated events.

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Paper III

Excerpt from: Safer Glances, Driver Inattention, and Crash Risk: An Investigation Using the SHRP 2 Naturalistic Driving Study

Phase II Final Report. Transportation Research Board of the National Academies, 2014.

This paper is an excerpt, with minor typographic editing and a few clarifying footnotes, of pages 117-128 from:

T. Victor, J. Bärgman, C.-N. Boda, M. Dozza, J. Engström, C. Flannagan, J. D. Lee, and G. Markkula. *Safer Glances, Driver Inattention, and Crash Risk: An Investigation Using the SHRP 2 Naturalistic Driving Study.* Phase II Final Report. Transportation Research Board of the National Academies, 2014.

Please refer to Section 2.3 of this thesis for additional background information regarding the rest of the report.

9.5 WHAT TRIGGERS DRIVERS' RESPONSES AFTER THE LAST GLANCE?

So far, the focus has been on what happens before and during the final off-road glance, and how this differs between crashes, near-crashes, and normal driving. A main insight has been that in many crashes (Category 1 in Figure 9.8[a]) the amount of change in situation kinematics during the final off-path glance (as determined by the interaction between glance duration and kinematics change rate) seems to be a main factor separating these crashes from near-crashes. However, there could also be differences between near-crashes and crashes in what happened after this final glance, a possibility that applies to all three categories of crashes in Figure 9.8. Investigating this possibility seems relevant, not the least for the crashes in Category 3, for which the analyses so far in this chapter have not shed any light on potential causes (besides some preliminary suggestions based on video inspection). This section looks specifically at the question of *when* drivers reacted to the rear-end situation, with the aim of answering the following questions:

- When, in relation to the situation kinematics, did drivers react? Were there differences between near-crashes and crashes in this respect?
- Do POV[b] brake lights predict timing of SV[c] driver reaction?

One tool used to answer these questions will be parameter-fitting and comparison of reaction timing models. The test of these models is in itself an additional aim here, since it is envisioned that they can be useful in future analyses, for example in Monte Carlo simulations to extrapolate from the findings in this chapter by studying a wide range of hypothetical rear-end situations, or to address "what-if" questions about the SHRP 2 events.

Throughout this section, "driver reaction point" refers to the manual annotation of "the first visible reaction of the SV driver to the POV [such as a] body movement, a change in facial expression etc."[d] This point of driver reaction does not necessarily coincide exactly with the initiation of an evasive braking or steering maneuver, but was adopted here due to difficulties in identifying the exact point of maneuver onset, partially caused by the lack of reliable data on pedal use (see section 4.9). From manual inspection

[a] Figure 9.8 of the original report is reproduced as Figure 2.5 of this thesis, on page 15.
[b] POV is short for principal other vehicle, i.e. the lead vehicle in the rear-end conflict situation.
[c] SV is short for subject vehicle; i.e. the following vehicle in the rear-end conflict situation.
[d] For further details, see Section 4.9 of the original report.

of the driver reaction point annotations, it is clear that in a great majority of cases this annotation is followed within some tenths of a second by signs of subject vehicle deceleration (but there are also some exceptions to this rule).

Table 9.4. *Exclusion of crashes and near-crashes for the analysis of driver reaction timing.*

Exclusion criterion	**Crashes excluded (% of total 46)**	**Near-crashes excluded (% of total 211)**
1. No annotated reaction before collision	5* (11%)	0
2. Time from last off-path glance to reaction > 8 s, or no off-path glances in event	3 (7%)	35 (17%)
3. Optical data not complete from end of last glance to extra-polated point of collision	3 (7%)	32 (15%)
4. No usable CAN or GPS SV speed data (missing or with apparent synchronization issues)	1 (2%)	14 (7%)
5. Annotated reaction with driver's eyes still off path	0	9 (4%)
6. Other apparent problems with the optical angle data	0	3 (1%)
7. Annotated reaction after minimum distance point	0	1 (<1%)
Total number of excluded events	12 (26%)	94 (45%)
Total number of included events	34	117

* In four of these five crash events, the driver's eyes were still off-path at collision.

The inclusion criteria adopted here (see Table 9.4) targeted the same type of scenarios as above in this chapter, but were stricter in order to allow parameter-fitting of models in the time plane. Matched baseline events were not included at all, since they did not have any annotated driver reaction points.

The difference in exclusion rate between crashes and near-crashes was mainly due to events with more than 8 s driving with eyes on path before reaction being more common among near-crashes than in crashes (criterion 2), optical data not being available all the way up to the point of extrapolated collision (see next section) in 21 near-crash events (criterion 3), and a manual effort to inspect the quality of GPS speed data in crashes without CAN speed data, allowing inclusion of three crash events that would otherwise have been programmatically excluded (criterion 4).

Driver reaction timing, situation kinematics, and brake lights

Figure 9.12 provides a first look at the extracted data, representing each event as a vertical gray line. Each such event line starts on the x-axis, at the event's invTTC[e] at the end of the last off-path glance (here and below denoted $invTTC_{ELG}$), passes through a black cross, showing the time from end of last glance to annotated driver reaction point, and ends at a blue dot, showing the time when a collision would have occurred, assuming that the driver did not react at all, in practice defined as a constant SV speed from the annotated driver reaction point (same approach as in Chapter 10).

First, consider the actual driver reaction points (the black crosses). For both crashes and near-crashes, two approximate regimes of behavior are discernible in this figure, to the left and right of an $invTTC_{ELG}$ = 0.2 s^{-1} threshold:

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[e] As in this thesis, invTTC is short for inverse time to collision.

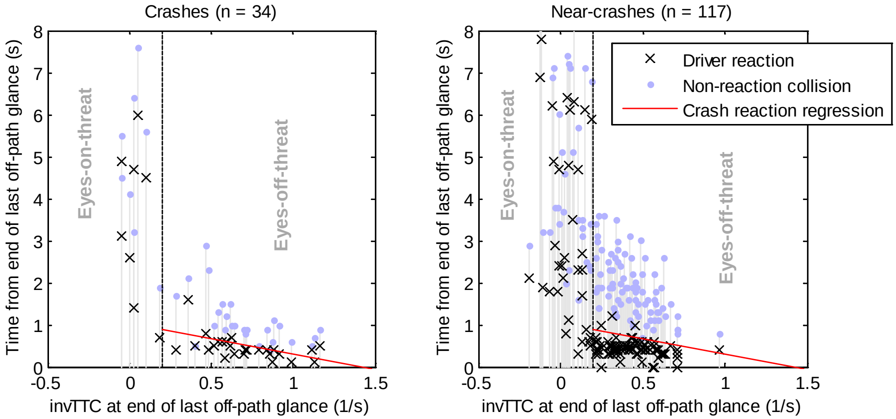

Figure 9.12 *Inverse TTC at the end of last glance ($invTTC_{ELG}$) versus time from the end of last glance to the driver reaction point and to extrapolated collision. A threshold $invTTC_{ELG}$ = 0.2 s^{-1} is shown as a vertical dashed line, and the regression line, fitted to reactions in* crash *events with $invTTC_{ELG}$ > 0.2 s^{-1}, is shown as a red line in* both *panels. Eyes-off threat crashes correspond to Category 1 and 2 in Figure 9.8 while eyes-off-threat correspond to Category 3.*

a) A clear majority of the long times to reaction > 1 s occurred for $invTTC_{ELG}$ < 0.2 s^{-1} (7 out of 8 for crashes; 27 out of 28 for near-crashes). This is consistent with the observation in the previous section that in some events, more specifically those in Category 3 of Figure 9.8, the driver did not find anything to react to at the end of the last off-path glance. Indeed, all of the crashes in Category 3 of Fig 9.8 do have $invTTC_{ELG}$ < 0.2 s^{-1}. As a shorthand throughout this section, events with $invTTC_{ELG}$ < 0.2 s^{-1} will be referred to as *eyes-on-threat* events, in line with the conclusion above in this chapter that in the Category 3 crashes, the rear-end threat arose *after* the last off-path glance.

b) A clear majority of all short times to reaction ≤ 1 s occurred for $invTTC_{ELG}$ > 0.2 s^{-1} (25 out of 26 for crashes; 82 out of 89 for near-crashes), suggesting situations where a threat arose some time before the end of the off-path glance, such that the driver found something to react to more or less immediately after the glance. Consistent with this idea, all of the crashes in Categories 1 and 2 of Figure 9.8 have $invTTC_{ELG}$ > 0.2 s^{-1}, and throughout this section events with $invTTC_{ELG}$ > 0.2 s^{-1} will be referred to as *eyes-off-threat* events. For these events, there are significant decreases in time to reaction with increasing $invTTC_{ELG}$ for both crashes ($r = -0.52$; $t(24) = 2.96$; $p = 0.007$; regression line shown in both panels of Figure 9.12) and near-crashes ($r = -0.25$; $t(81) = 2.30$; $p = 0.024$; regression line not shown in Figure 9.12).

Given the aims of this section, it is interesting to note that for eyes-off-threat near-crashes (i.e. the near-crashes with $invTTC_{ELG}$ > 0.2 s^{-1}), driver reaction points seem to group *below* the regression line for eyes-off-threat crashes (the red line in both panels of Figure 9.12). To verify this impression, deviations from this regression line were compared between crashes and near-crashes, and were found to have significantly different averages ($t(107) = -4.020$; $p = 0.0001$), with near-crashing drivers reacting, on average, 0.19 s faster than what is predicted by the regression line for crashes.

Next, consider the blue dots, showing the time, after end of last off-path glance, of non-reaction collision. This time duration can be regarded as a crude estimate of situation urgency at the end of the last off-path glance, and there are two observations to be made here: First, the times to non-reaction collision seem shorter in crashes than in near-crashes. If so, this would mean that not only was $invTTC_{ELG}$ higher, on average, for crashes than for near-crashes (as shown in Figure 9.4), but also for a given $invTTC_{ELG}$ the situation grew worse faster for crashes, e.g., due to larger POV decelerations. As a crude test of this possibility, times to non-reaction collision in the $invTTC_{ELG}$ interval [0.4, 0.7] s^{-1} (where there is a reasonable coverage of both crashes and near-crashes) were compared and found to be lower for crashes (1.4 s) than for near-crashes (1.7 s), but this difference is not statistically significant ($t(48) = -1.268$; $p = 0.21$). A similar test for the eyes-on-threat crashes (with $invTTC_{ELG} < 0.2\ s^{-1}$) also comes up non-significant (average times to extrapolated collision 4.9 s and 4.7 s for crashes and near-crashes; $t(40) = 0.188$; $p = 0.85$).

Second, it should be noted that in most crash events, there are time margins *after* the observed reaction point within which reaction *could* have occurred and still preceded a collision, in some cases up to two seconds. This observation, together with the fact that only one non-reaction with eyes on path was observed among the 46 crashes in the total data set (see Table 9.4), suggests that if a driver looks forward, he or she will generally react, at least in the “first visible reaction” sense, to a rear-end threat before the actual crash. This makes a very strong case for the hypothesis that situation kinematics, e.g. mediated by visual looming, have an impact on the timing of driver reactions.

The analysis above (Table 9.1) indicated that drivers in crashes and near-crashes generally tended to ignore the onset of brake lights as a cue that the lead vehicle is likely to become a threat in the near future. Nonetheless, it is still possible that the lead vehicle brake lights had an influence on driver reactions once the situation became critical (i.e., after the end of the last glance). However, in most crashes (74%) and near-crashes (79%), POV brake lights were on all the way from end of last glance to the driver reaction point, so it is clear already from Figure 9.12 that, in general, the drivers did not react with some fixed, situation-independent reaction time to the sight of already illuminated brake lights. Figure 9.13 shows driver reaction points in the (rather few) events where one or more brake light *onsets* occurred between end of last glance and the driver reaction point, and the figure also shows where in time the last brake light onset occurred (the start of the red lines). A possible reason for the difference between crashes and near-crashes starting at $invTTC_{ELG} < 0.2\ s^{-1}$ (i.e. the eyes-on-threat events, corresponding to Category 3 of Figure 9.8) could have been that near-crashing drivers in these events were more successful than crashing drivers at responding to brake light onsets. However, the data shown in Figure 9.13 do not provide any strong support for this idea: Among the five eyes-on-threat crashes, driver reaction came within 1 s after brake light onset in one case (20%). For near-crashes, the same figure was 7 out of 20 (35%), a difference that was not statistically significant ($p = 0.47$; Fisher’s exact test). In the other crashes and near-crashes shown in Figure 9.13, reaction came anywhere up to six or seven seconds after the last brake light onset, such that the general impression from Figure 9.13 is that brake lights onsets had rather little to do with the timing of driver reactions in the present crashes and near-crashes.

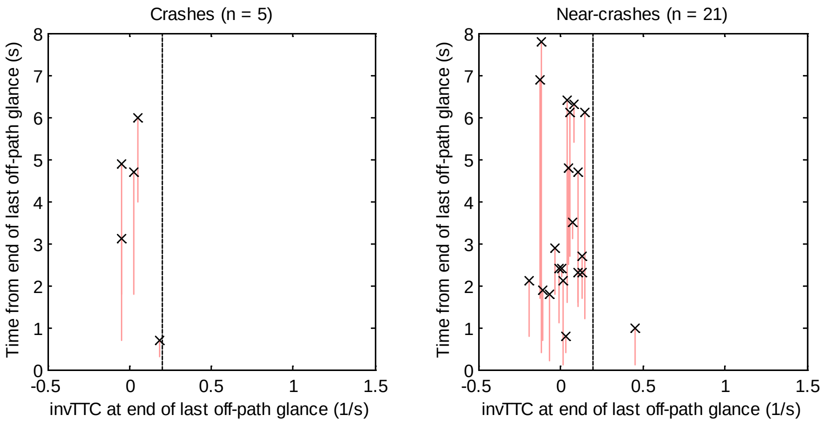

Figure 9.13. *As Figure 9.12 but showing only events with one or more brake light onsets between end of last glance and the driver reaction point. The red stripes begin at the time of last brake light onset, and, for clarity, end at the driver reaction point (regardless of whether or not the brake lights remained on all the way up until this point).*

Thus, so far the results indicate that brake lights had a limited effect on reaction timing, but that reactions were instead strongly related to kinematics, at least in the sense that driver reaction always occurred (with only one exception) before the actual crash, and typically with quite some time margin left to when a non-reacting driver would have crashed. Fig 9.14 provides further insight into the relationship between kinematics and reactions, by showing both invTTC at the end of last glance (on the x-axis, as above), and invTTC at the driver reaction point, referred to here as $invTTC_R$ (on the y-axis). A diagonal y=x line is shown; a reaction on this line implies an event where invTTC was the same at the end of last glance and at the reaction. As in Figure 9.12, there are signs of qualitative differences between eyes-on-threat and eyes-off-threat events, and there are traces of the same 0.2 s^{-1} threshold also for $invTTC_R$. In the figure, both of these thresholds are shown, as one vertical and one horizontal line.

a) To the left of the vertical line in the figure, i.e., for the eyes-on-threat events (with $invTTC_{ELG} <$ 0.2 s^{-1}), there is a vertical gap from the diagonal y=x line up to the horizontal line, above which almost all reactions occur, with some variability. This signifies that in both crashes and near-crashes, reactions generally did not occur before the kinematics had evolved to at least a level of 0.2 s^{-1} invTTC. Specifically, for these crashes and near-crashes, average $invTTC_R$ was 0.49 s^{-1} and 0.45 s^{-1}, respectively, a non-significant difference ($t(40) = 0.479$; $p = 0.63$).
b) To the right of the vertical line, i.e. for the eyes-off-threat events (with $invTTC_{ELG} > 0.2$ s^{-1}), driver reactions are present directly from the diagonal y=x line, again with variability, creating a diagonal band of points in the plot both for crashes and near-crashes. This band seems to have a larger vertical spread for crashes than for near-crashes. Indeed, the average of $invTTC_R$ - $invTTC_{ELG}$, i.e. the height of reactions over the y=x line, was significantly larger ($t(107) = 6.182 < p$ 0.0001) for crashes (0.32 s^{-1} average increase) than for near-crashes (0.13 s^{-1} average increase). In other words, even for comparable situation kinematics at the end of last glance, crashing drivers reacted, on average, at a point in time with more severe kinematics than near-crashing drivers.

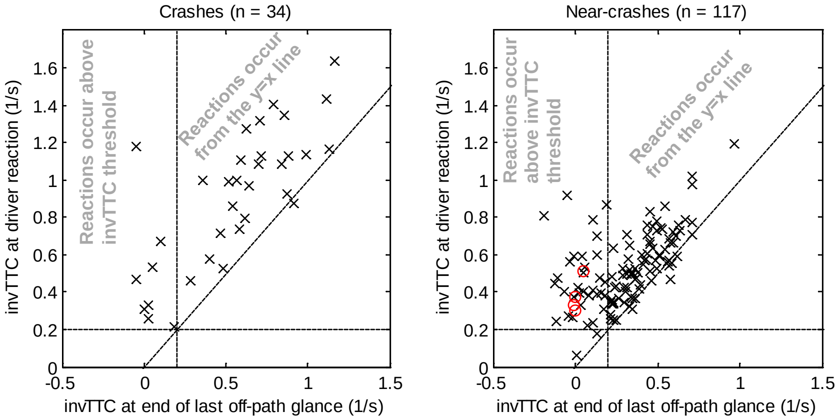

Figure 9.14. *InvTTC at the end of the last off-path glance (invTTC$_{ELG}$) versus invTTC at the driver reaction point (invTTC$_R$), for crashes and near-crashes. In the right panel, red rings show driver reactions in the four near-crashes where the driver talked or listened on a cell phone. One of these four cell phone events (at invTTC$_R$ $\approx$ 0.5) represents an event that was included in the other analyses of this section, while the other three were originally excluded (see Table 9.4) due to time to reaction being over 8 s (one case), or no optical cues being available at the end of the last off-path glance (two cases; shown at invTTC$_{ELG}$ = 0 in the figure since both were clear eyes-on-road, i.e. Category 3, events).*

Another way of formulating this last result is that, on average, in eyes-off-threat events, the situation changed more for the worse in crashes than in near-crashes during the time interval from end of last glance to the driver reaction point. This is analogous to what was found in the previous section regarding changes in kinematics during the last off-path glance, and again both time (here, time to reaction) and kinematics change rate could play a role. Here, it has already been observed, in relation to Figure 9.12, that for eyes-off-threat events, driver reactions were, on average, significantly slower in crashes than in near-crashes, and that there was a possible, non-significant trend of times to extrapolated collision being shorter in crashes than in near-crashes (i.e. implying a faster kinematics change rate). Both of these observations align with the observed difference in total change in invTTC from end of last glance to the driver reaction point.

Driver reactions when talking or listening on a cell phone

As mentioned above, several naturalistic driving studies have found cell phone conversation to have a protective effect (Olson et al., 2009; Hickman, Hanowski and Bocanegra, 2010). The present study found an even stronger protective effect with an odds ratio for talking or listening on the phone of 0.1 (see Section 6.1). To investigate to what extent this effect is related to changes in driver reactions induced by phone conversation, the four near-crash events where the driver was coded as "talking/listening on cell phone" are plotted in the right panel of Figure 9.14 along with the other events where the driver was not in a phone conversation (as described in Section 6.1, there were no crashes in the present sample with "talking/listening on cell phone" coded).

First, it may be noted that all four near-crashes with talking or listening on the cell phone are of the eyes-on-threat type (i.e., Category 3 above). Second, as can be observed in Figure 9.14, there are no indications that the cell phone conversation affect reactions to the rear-end threat; these drivers react at about the same kinematic severities as the other nearly crashing drivers. Average invTTC_R for the four drivers who talked or listened on their cell phones was 0.38 s^{-1}, which is actually lower than the average 0.45 s^{-1} for the other eyes-on-threat near-crashes. However, the difference was non-significant ($t(35) = -0.708$; $p = 0.48$).

Underlying mechanisms and model-fitting

Again recapitulating, driver reactions in the SHRP 2 crashes and near-crashes are strongly associated with situation kinematics. Reactions are almost never observed for invTTC below 0.2 s^{-1}, but above this threshold reactions almost always occur before collision, which in practice means that at progressively higher invTTC_{ELG}, the reactions are progressively faster.

A candidate mechanism that could account for this set of observations is *evidence accumulation*. In psychology and neuroscience, models that assume that overt actions are triggered once evidence for their suitability have accumulated to a threshold (also known as *diffusion* or *race* models) have been found to account well for reaction time distributions in a wide variety of tasks (Gold and Shadlen, 2007; Ratcliff & Van Dongen, 2011), including brake reactions to expected activations of lead vehicle brake lights (Ratcliff & Strayer, 2013). Potential neural correlates of such processes have also been identified (Gold and Shadlen, 2007; Purcell et al., 2010). Markkula (2014) hypothesized that timing of brake responses in driving could be driven by accumulation of the various cues that signal the possible need of deceleration (e.g. contextual, augmenting and primary cues, in the terminology of Tijerina et al., 2004). Here, using the same type of accumulator as Markkula (2014), and, for simplicity, assuming accumulation of invTTC, driver reaction could be hypothesized to occur when an activation $A(t) \geq 0$, changing over time as:

$$\frac{dA(t)}{dt} = \text{invTTC}(t) - M + \varepsilon(t) \tag{9.1}$$

has risen above a threshold A_t. Here invTTC is used, however but inverse tau could also equally be used (but here these two are the same; see above in this section. Also, see e.g. Flach et al., 2004; Kiefer et al., 2005, or Fajen, 2008 for alternative visual cues to consider). Markkula (2014) suggested that the model parameter M could be regarded as the sum of the influence from all other cues, e.g. contextual cues, and that it therefore could be affected by factors such as attention or expectancy. $\varepsilon(t)$ is a noise term, e.g. normally distributed, relating to inherent variability in underlying neural activity. It may be noted that for a given parameterization of the model as formulated above:

- No reactions will be generated as long as invTTC is sufficiently below M (sufficiently below given the variability of $\varepsilon(t)$).
- Above M, larger values of invTTC will cause activation to reach threshold faster.

In other words, qualitatively, the model is completely in line with what has been observed here.

To test these ideas in practice, the model in Equation 9.1 was parameter-fitted to the crash and near-crash data separately, by means of a genetic algorithm (GA; see, for example, Wahde, 2008) optimizing parameters to minimize Δ_{RMS}, the root mean square deviation between observed and predicted times of reaction. $\varepsilon(t) = 0$ was used, to allow this type of deterministic simulation and model-fitting (rather than e.g. maximum likelihood model-fitting). This approach can provide a first idea of the usefulness of the model, but perfect fits should not be expected, since a deterministic model with one shared parameterization for all events cannot at all account for natural variability in reaction times (non-zero $\varepsilon(t)$), or variations between events in driver attention or expectancy (varying M).

For each event, the model was fed the invTTC history starting from end of last glance, and to allow meaningful fitting of model reactions occurring later than the observed reactions, the effect of driver avoidance maneuvering on invTTC was removed, as mentioned above, by assuming a constant SV vehicle speed after the annotated point of driver reaction. To reduce the risk of obtaining local optima, each optimization was repeated three times, with 500 GA generations in each repetition, and reasonable optimization convergence was subjectively verified by inspection of model-fit time histories.

Figure 9.14 shows the fit of the model to the crash and near-crash data, together with the coefficients of determination R^2, interpretable as the amount of variance explained by the model, computed as:

$$R^2 = 1 - \frac{SS_E}{SS_T} = 1 - \frac{\sum_i \left(T_{i,\mathrm{model}} - T_{i,\mathrm{observed}}\right)^2}{\sum_i \left(T_{i,\mathrm{observed}} - \bar{T}_{\mathrm{observed}}\right)^2}$$

where $T_{i,\mathrm{observed}}$ are the observed times to reaction, with average $\bar{T}_{\mathrm{observed}}$, and $T_{i,\mathrm{model}}$ are the corresponding model predictions. Negative values for R^2 thus imply that the model produces larger prediction errors than what would be obtained for a fixed prediction $T_{i,\mathrm{model}} = \bar{T}_{\mathrm{observed}}$ for all events.

Figure 9.15 shows that for both crashes and near-crashes, the accumulator model is rather successful at predicting times to reaction (R^2 = 0.95 and R^2 = 0.93, respectively, root mean square error of predicted reaction timing $\Delta_{RMS} \approx 0.4$ s) when considering the entire sets of data, in which the variability is dominated by the long times to reaction of the eyes-on-threat crashes. If singling out only the shorter times to reaction of the eyes-off-threat crashes ($\mathrm{invTTC}_{ELG} > 0.2\ \mathrm{s}^{-1}$; bottom left panel of Figure 9.15), the coefficient of determination is more modest (R^2 = 0.24), but it should be noted that it is comparable to what was obtained for the linear correlation in Figure 9.12 (R^2 = 0.27). This can be interpreted as the model indeed providing a possible underlying mechanism behind that linear correlation, but not having any further explanatory power beyond it (and, as mentioned above, no means of accounting for e.g. variations in attention or expectancy). When fitting the model to only the eyes-off-threat events, a slightly better fit, with Δ_{RMS} = 0.24 s and R^2 = 0.28 was obtained.

For the eyes-off-threat near-crashes, the linear correlation in Figure 9.12, was, although statistically significant, even weaker than for the crashes (R^2 = 0.06), and this weak correlation was, as is clear from Figure 9.14 (bottom right panel), not recreated by the accumulator model. Also here, fitting to only the $\mathrm{invTTC}_{ELG} > 0.2\ \mathrm{s}^{-1}$ subset yielded an improved model fit, Δ_{RMS} = 0.20 s, however still with a negative coefficient of determination(R^2 = -0.04).

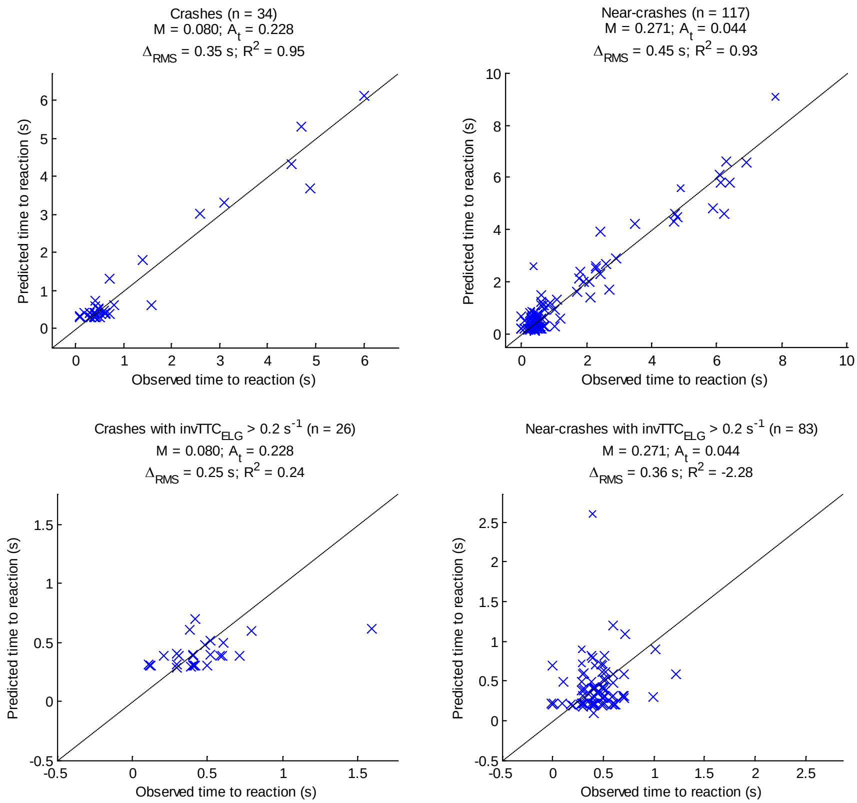

Figure 9.15. *Fits of the accumulator model to observed reactions, in crashes and near-crashes. The top two panels show the full sets of data used for model-fitting. The bottom two-panels provide a zoomed-in view of the events with invTTC at the end of last glance > 0.2 s^{-1}.*

The fact that the accumulator model was less able to fit the times to reaction in eyes-off-threat near-crashes than in the eyes-off-threat crashes could be taken to imply that there were some differences in mechanisms between these crashes and near-crashes, which the model doesn't cover. Another possibility may be that a type of selection bias comes into play here, making any signs of evidence accumulation difficult to discern: While the driver reactions in the crash events did not seem tightly constrained by the fact that they need to lead to collisions to be included in the data set (as discussed in relation to Figure 9.12), reaction timing in near-crashes is constrained both from above (must be early enough to avoid crash) and from below (must be late enough to generate a near-crash). In other words, the SHRP 2 vehicles may have been involved in many driving events with similar kinematics to the present near-crash events, but which nevertheless did not register as near-crashes because the driver happened to react slightly faster (in the terms of the model, due to favorable ε, or a lower M), or which instead registered as a crash because of a slightly later reaction. If so, this could mean that variability in observed near-crash driver reactions may be dictated more by the kinematic constraints of near-crash-detecting triggers and crash avoidance feasibility, than by actual driver behavior phenomena.

As a contrast to the accumulator model, another two-parameter model was also fitted, instead predicting a driver reaction a fixed reaction time delay T_R after passing an invTTC threshold. At long times to reaction, this is a very close approximation of the accumulator model (with M as the invTTC threshold, and accumulation to A_t as a delay), and as could therefore be expected this simpler model also worked well for the eyes-on-threat events, with long times to reaction (overall Δ_{RMS} = 0.38 s and R^2 = 0.94 for crashes; Δ_{RMS} = 0.43 s and R^2 = 0.94 for near-crashes). However, for the shorter times to reaction of the eyes-off-threat events this model will almost always predict a time to reaction of T_R, yielding poor fits (Δ_{RMS} = 0.29 s and R^2 = -0.04 for crashes; Δ_{RMS} = 0.33 s and R^2 = -1.74 for near-crashes) and reinforcing the idea that something akin to evidence accumulation is needed to explain the effect of situation kinematics on times to reaction in eyes-off-threat events.

Finally, consider the parameter values obtained for the accumulator model when fitted to crashes and near-crashes. The mere observation that the parameter values differ do not provide much information, since M and A_t are to some extent redundant (a higher M can be partially compensated for by a lower A_t, and vice versa). Therefore, analogously to what was done for the linear correlation in Figure 9.12 Figure 9.16 shows the results of applying the accumulator model obtained for near-crashes to the crash events. For the eyes-off-threat crashes, with short times to reaction, the model fitted to near-crashes predicted faster reactions than the model fitted to crashes, and the average difference of0.22 s is well in line with the 0.19 s difference observed in relation to Figure 9.12. For the eyes-on-threat crashes, with longer times to reaction, prediction deviations went in both directions, adding up to the near-crash model predicting, on average, 0.01 s shorter times to reaction. This is in line with the apparent lack of difference in reaction timing between eyes-on threat crashes and near-crashes observed in Figure 9.14.

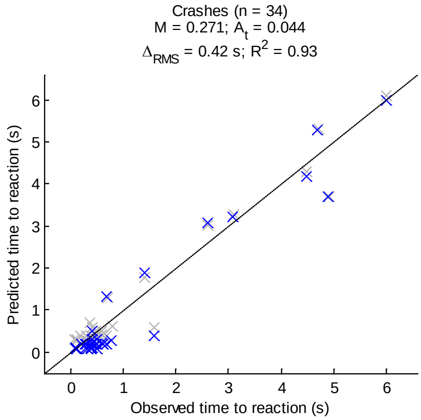

Figure 9.16. *Comparison of the fits of crash data for the crash model (gray crosses, same as in the top left panel of Figure 9.15) and the near-crash model (blue crosses, parameters as in the top right panel of Figure 9.15).*

Summary

In conclusion, it has been shown that driver reactions in the SHRP 2 crashes and near-crashes were not notably affected by POV brake lights, but were instead strongly coupled to situation kinematics. It was found that the categories of crashes in Figure 9.8 could be neatly separated by a threshold of $invTTC_{ELG}$ at the end of the last off-path glance: The eyes-off-threat crashes (Category 1 and 2) all had $invTTC_{ELG} > 0.2$ s^{-1}, and the eyes-on-threat crashes (Category 3) all had $invTTC_{ELG} < 0.2$ s^{-1}. For eyes-on-threat events (both crashes and near-crashes), very few reactions occurred before reaching an invTTC of at least 0.2 s^{-1}, meaning that the reaction could occur an arbitrarily long time after the last off-path glance. In contrast, for eyes-off-threat events (again, both crashes and near-crashes), the driver reactions almost always came within a second, and almost always before the crash, in practice implying that reactions were faster in situations with high $invTTC_{ELG}$.

It has been explained that an accumulator model of reaction timing, accumulating invTTC once invTTC has reached a minimum threshold, would, qualitatively, predict exactly these observations (no reactions below an invTTC threshold, and progressively faster reactions above it). In actual model-fitting to the observed reactions, a simple two-parameter accumulator was found to account acceptably well for reaction variability in crash events (both eyes-off-threat and eyes-on-threat) and in eyes-on-threat near-crash events, however not in eyes-off-threat near-crashes. This could possibly relate to issues of selection bias, which make model-fitting to this type of naturalistic data challenging in general.

There are clear signs that, for eyes-off-threat events, near-crashing drivers reacted, on average, about 0.2 s faster than crashing drivers, and there are possible indications that the crash events in this regime also evolved to higher severity faster than comparable near-crashes. This implies that causation of eyes-off-threat crashes could be further understood as involving a) kinematics that changed faster than in similar near-crashes also *after* the end of the last off-path glance (not statistically proven here), and b) drivers that for some reason had slower reactions (statistically significant). These slower driver reactions could be a result of natural variability in reaction timing, where slightly slower reactions happened to lead to crashes, and slightly faster reactions did not. However, the descriptive data analysis (Chapter 5) identifies a number of factors that were overrepresented in crashes, such as young age, rain, visual obstructions etc., factors which could be hypothesized to be associated with slower reactions in critical situations. Another factor that could be expected to influence driver reactions is the degree to which the driver's expectancy was violated (Green, 2000); it is possible that crashes on average involved situations where the driver was more certain that the lead vehicle would not brake, leading to a longer time to reaction. Finally, one aspect which has not been considered in the analyses presented here, is the possibility of drivers acquiring some information about the impending rear-end situation via peripheral vision (Lamble et al., 1999; Markkula, 2014). This could be needed to convincingly explain some of the very short and even zero times to reaction occurring in some eyes-off-threat events, especially in near-crashes.

For the eyes-on-threat crashes, the analyses in this section did not identify any specific differences from comparable near-crashes that could serve as clues regarding crash causation. Here, no clear signs of slower reactions from crashing drivers were found, and no clear signs of situation kinematics evolving faster in crashes than in near-crashes. Moreover, drivers involved in cell phone conversation did not respond at higher invTTC (looming) values than the other near-crash involved drivers. Overall, these results suggest that what separates eyes-on-threat crashes from comparable near-crashes may be related to failures to apply crash-avoidance braking or steering maneuvers after the point of driver reaction. This could involve differences in the time from observed driver reaction (such as studied here) to initiation of actual maneuvering, but also differences in factors such as actual maneuvering capacity of the vehicle on the road (e.g. relating to vehicle brakes, road surface friction etc.), space available for lateral maneuvering, or the extent to which the drivers utilized the full maneuvering capabilities of the vehicle.

[…]

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Paper IV

A review of near-collision driver behavior models

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A review of near-collision driver behavior models

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Objective: This paper provides a review of recent models of driver behavior in on-road collision situations.
Background: In the efforts to improve traffic safety, computer simulation of accident situations holds promise as a valuable tool, both for academia and industry. However, in order to ensure the validity of simulations, models are needed that accurately capture near-crash driver behavior, as observed in real traffic or driving experiments.
Method: Scientific papers were identified by a systematic approach, including extensive database searches. Criteria for inclusion were defined and applied, including the requirement that models should have been previously applied to simulate on-road collision avoidance behavior. Several selected models were implemented and tested in selected scenarios.
Results: The reviewed papers were grouped according to a rough taxonomy based on main emphasis, namely: Avoidance by braking, avoidance by steering, avoidance by a combination of braking and steering, effects of driver states and characteristics on avoidance, and simulation platforms.
Conclusion: A large number of near-collision driver behavior models have been proposed. Validation using human driving data has often been limited, but exceptions exist. The research field appears fragmented, but simulation-based comparison indicates that there may be more similarity between models than what is apparent from the model equations. Further comparison of models is recommended.
Application: This review provides traffic safety researchers with an overview of the field of driver models for collision situations. Specifically, researchers aiming to develop simulations of on-road collision accident situations can use this review to find suitable starting points for their work.

Keywords: driver behavior, models, simulation, collisions, accidents, crashes, avoidance

Road traffic accidents are a global problem, causing enormous economic and social costs, and more than a million fatalities every year (World Health Organization, 2009). A considerable proportion of severe accidents involve on-road collisions (see e.g. Najm, Smith, & Yanagisawa, 2007). It is widely accepted that the behavior of vehicle drivers contributes strongly to accident causation, and much research effort has therefore been directed at understanding the relationship between driver behavior and safety, as well as what can be done to avoid or improve behaviors associated with crashes (J. D. Lee, 2008).

A time-honored approach in these endeavors has been the description and prediction of human driver behavior by means of *models* (see e.g. Gibson & Crooks, 1938). In recent years, some traffic safety researchers have applied *quantitative* driver behavior models in *computer simulation*. For example, simulation of road networks with many simulated drivers has been used to study the potential safety impact of envisioned infrastructure improvements (see, for example, Saka & Glassco, 2001). Also, estimates of the expected reduction of accidents from driving support technology, such as collision warning systems, have been obtained from computer simulations of the final seconds leading up to a crash (see e.g. T. Brown, Lee, & McGehee, 2001).

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In general, computer simulation can provide a means of obtaining data regarding a system under study in a manner that is more controlled, repeatable, cheap, fast, and safe than obtaining similar data from real-life measurements. As a consequence, simulations may allow more powerful statistical analyses, or more complete testing and comparison of large numbers of alternative system designs. Computer simulations therefore hold great promise as an important tool for traffic safety research and development, both within industry and academia.

However, there is one general constraint: The results of simulations will never be more valid than the models on which the simulations are based. In order to realize any of the above-mentioned benefits of computer simulation of accidents, a crucial requirement is the availability of well-defined, quantitative models that accurately capture the behavior of drivers in the considered accident situations.

A number of authors have reviewed the driver modeling literature, from various perspectives (Reid, 1983; Michon, 1985; Ranney, 1994; Ghazi Zadeh, Fahim, & El-Gindy, 1997; Brackstone & McDonald, 1999; Helbing, 2001; MacAdam, 2003; X. Wang, Yang, Shan, & Wang, 2006; Cody & Gordon, 2007; Plöchl & Edelmann, 2007; Weir & Chao, 2007; Jürgensohn, 2007; Oppenheim et al., 2010). Among these, only Reid (1983) focused specifically on the modeling of accident-related driving behavior, concluding that at the time of writing there was "no well-developed and validated model for the detailed study of accidents" (p. 23). The other listed reviews all addressed models of driving behavior in general, with no specific focus on accident situations, and many also focused on models that were qualitative rather than quantitative, or models that for other reasons were not specified to the extent needed for implementation in computer simulation.

The aim of this review is to describe recent *simulation-ready models of driver behavior in accident situations involving on-road collisions*. The limitation to on-road collision accidents is adopted to keep the review manageable in size.

The remainder of the text will be organized as follows: First, some background will be provided on current theory and empirics regarding on-road collision accidents. Then, the method for identifying suitable models to review will be presented, including inclusion and exclusion criteria. Next, the identified models will be presented. In a concluding section, the models will be discussed and compared to the theoretical and empirical accounts of accident causation. Some suggestions for future work will be given as well.

Background

A brief presentation regarding theoretical and empirical results on driver behavior in near-collision situations will now be given, in order to provide a general outline of the reality that the driver models reviewed in this paper typically should aim to reproduce.

Based on U.S. accident statistics, Najm et al. (2007) proposed a typology of 37 pre-crash scenarios. A majority of these involved on-road collisions, with motor vehicles, cyclists, pedestrians, animals or other objects, occurring both at intersections and non-intersection locations. Examples of collision accident classes that can be found in the paper are: (a) *rear-end collisions*, with sub-classes *lead vehicle decelerating* (LVD), *lead vehicle moving* (LVM), and *lead vehicle stationary* (LVS); (b) *intersection collisions*; and (c) *head-on collisions*.

As a support when reasoning about the transition from normal driving into accidents, many authors have introduced divisions of the pre-crash timeline into a sequence of states. The division adopted by Najm and Smith (2004) is shown in the left part of Figure 1.

Non-critical collision avoidance

In everyday driving, a driver will routinely pass from a *low risk* state into the *conflict* state, for example whenever a slower moving lead vehicle is encountered, and then back again to the low risk state as a result of successful use of acceleration, deceleration, steering, or a combination thereof.

Several accounts have been proposed regarding how such everyday collision avoidance is achieved. A recurring concept in these is *satisficing*: Drivers will normally not apply collision avoidance at the very instant a collision course is established (which could be referred to as *optimizing*), but instead at some later time, related to the *safety margins* of the driver (see e.g. Summala, 2007).

D. Lee (1976) introduced the quantity $\tau = \theta/\dot{\theta}$, where θ is the angle subtended by an obstacle on the driver's retina, and demonstrated that τ is a close estimate of *time to collision* (TTC). Furthermore, he proposed that drivers initiate braking when τ passes a certain threshold, independent of speed, and he also demonstrated how $\dot{\tau}$, the time derivative of the same quantity, could hypothetically be used during control of braking. Fajen (2005, 2008) proposed another model, integrating satisficing aspects also in the control of an ongoing braking

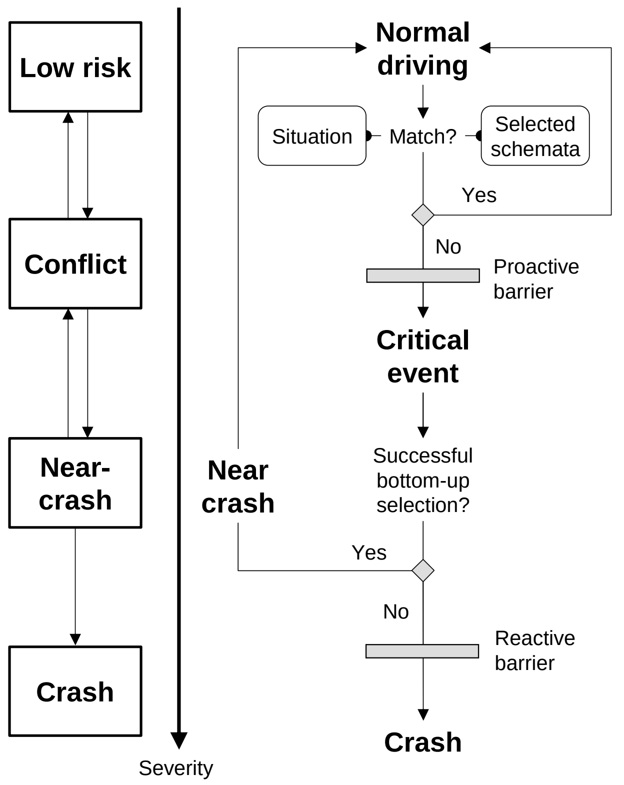

Figure 1. : The four driving conflict states adopted by Najm and Smith (2004), alongside the crash causation model of Engström et al. (in press).

maneuver. Kiefer, LeBlanc, and Flannagan (2005) analyzed a large dataset of test track driving, and found that test subject brake initiation could be described as occurring at a speed-dependent threshold for inverse TTC, decreasing linearly with increasing speed.

Timing of steering initiation in normal avoidance may be subject to the same general patterns, although with later timing than braking responses (Kiefer et al., 2005; Najm & Smith, 2004). As for braking, models are available regarding the visual cues that are used by drivers during steering, and how these cues are translated into control actions (Land & Horwood, 1995; Wann & Wilkie, 2004).

It has been repeatedly observed that drivers are capable of adapting their control behavior to the specific vehicle they are driving (MacAdam, 2003). Nevertheless, experiments on open-loop control (where drivers are deprived of visual and inertial feedback) also suggest that drivers' understanding of the dynamics of their vehicles may be fundamentally limited (Cloete & Wallis, 2009).

Transitions to critical collision events

Sometimes, normal driving passes into more critical states. A *near-crash* state can be defined, for example, in terms of the kinematics of the momentary traffic situation (Najm & Smith, 2004), or in terms of the severity of required avoidance maneuvering (S. E. Lee, Llaneras, Klauer, & Sudweeks, 2007). The *crash* state can be regarded as being reached when it is no longer possible to avoid the collision.

It is still a matter of scientific debate exactly *why* these transitions from normal to critical driving sometimes occur. Accident statistics and empirical studies point to many factors that correlate with accident risk, such as fatigue, alcohol intoxication, distractions, age, driving experience, and driving style (see e.g. J. D. Lee, 2008 for an overview), and a variety of competing qualitative models have been proposed for explaining how these factors come into play.

One view is available from *information processing* models of human behavior. In this paradigm, human behavior in general has been described as the result of information processing along a sequence of stages, for example: (a) sensory processing, (b) perception, (c) cognition and memory, (d) response selection, and (e) response execution (Wickens & Hollands, 2000). Accidents have been modeled as due to *errors*, occurring at different points along the sequence of processing, causing degradation of the normal behavior in the form of, for example, *slips*, *lapses*, or *mistakes* (Wickens & Hollands, 2000). The frequency of such errors can then be assumed to vary with accident-related factors such as those listed above. van Elslande and Fouquet (2007) provided one example of how a model based on information processing can be applied in the study of traffic accident causation.

Alternatives to this type of model exist and one example, focusing mainly on the role of attention in accident causation, is illustrated alongside the pre-crash timeline division in Figure 1. This model is due to Engström, Victor, and Markkula (in press; see also Engström, 2011), who discussed driver behavior using the metaphor of *schemata*, "functional units of action control at different levels of abstraction" (p. 38), such as for example *recognize traffic light*, or *follow the car ahead*. They hypothesized that, under normal circumstances, proper schemata selection (based on the driver's understanding of how the traffic situation will evolve in the near future) is sufficient to avoid critical events. Engström et al. referred to this mechanism as a *proactive barrier*, and proposed that it fails when there is a mismatch between the selected schemata and the traffic situation at hand, such that early conflict resolution is either unsuccessful or absent altogether. Candidate factors which could be hypothesized to increase the risk of such mismatches include *infrequent events*, *misleading contextual cues*, and *cognitive distractions*. For example, cognitive distraction has been observed to impair driver ability to adapt gap acceptance judgments to road conditions, when turning at an intersection (Cooper & Zheng, 2002), and in straight-line collision situations, unexpected braking stimuli and cognitive distractions have been empirically linked with later brake reactions (Green, 2000; Salvucci, 2002).

In the model proposed by Engström et al., when the proactive barrier fails, the crash may still be prevented by the *reactive barrier*: Visual stimuli, such as the *looming* of the obstacle on the retina, are hypothesized to cause *bottom-up* reflex activation of near-crash avoidance schemata. Recent naturalistic driving studies have highlighted the strong relationship between *visual distraction* and crashes (see e.g. Dingus et al., 2006; S. E. Lee et al., 2007), and Engström et al. proposed that these observations could be understood in terms of the reactive barrier failing when the driver's gaze is off the road ahead. It has been shown that the most common driver behavior in rear-end crashes is no maneuver at all (S. E. Lee et al., 2007; Wiacek & Najm, 1999), and in accident statistics this was linked to driver distraction by Yan, Harb, and Radwan (2008).

Critical collision avoidance

Models of why a near-crash collision situation may arise, such as outlined above, can be complemented with models of more exactly *when* and *how* near-crash collision avoidance maneuvering is then carried out by the driver.

Maneuver timing has been studied by many researchers, in terms of the *reaction time* from a stimulus to an evasive reaction, and reaction time estimates have been proposed as functions of a range of parameters: Stimulus eccentricity, number of obstacles, nighttime versus daytime driving, age, gender, as well as the above-mentioned cognitive distraction and stimulus expectancy (Delaigue & Eskandarian, 2004; Green, 2000; Muttart, 2003; B. Wang, Abe, & Kano, 2002). In addition, limitations on *just noticeable differences* of changing stimuli, as prescribed by Weber's law (Gray, 2010, p. 263), have also been discussed as introducing constraints regarding the earliest time at which a driver can react to a change in the traffic scene (see e.g. D. Lee, 1976).

As for the manner in which drivers carry out critical collision avoidance maneuvering, braking only (without steering) has been identified as the most natural first response for most drivers, and steering (alone or with braking) has been observed more frequently at low values of TTC, such that the driver may perceive that braking is insufficient to avoid the crash (Adams, 1994; S. E. Lee et al., 2007; Wiacek & Najm, 1999)[1].

Several researchers have noted a tendency of drivers not to apply steering to the full stability limits of their vehicles, and to brake and collide in situations where steering could have avoided the collision. It has been proposed that such behavior may be due to (a) drivers having very little experience of applying high lateral accelerations, or (b) perceived added risks from abruptly steering away from one's own lane (Adams, 1994; Lechner & van Elslande, 1997). Breuer (1998) compared normal driving in real traffic with driving in a double lane change maneuver (similar to that of ISO, 1999), and argued that the high lateral accelerations induced in such test track maneuvers are very rare in real traffic.

Braking at the vehicle's limits seems more common (Lechner & van Elslande, 1997; McGehee et al., 1999), but also in this context it has been argued that lack of experience of, and low expectancy for, critical braking may limit the magnitude of avoidance maneuvering employed by drivers (Dilich, Kopernik, & Goebelbecker, 2002).

In general, an important question is whether the models of non-critical collision avoidance presented earlier are valid in more critical situations. Hollnagel and Woods (2005, p. 146) defined different *control modes* and argued that, whereas control often relies on anticipation and planning (*tactical* and *strategical* control modes), in more urgent or unusual situations control may rather be driven by salient features of the immediate situation (*opportunistic* control mode) or even become random (*scrambled* control mode). This relates clearly to the above-mentioned observations of non-response behavior in crashes (S. E. Lee et al., 2007; Wiacek & Najm, 1999), and also to reports from accident reconstructions on driver control overreactions (Malaterre, Ferrandez, Fleury, & Lechner, 1988).

[1] S. E. Lee et al. (2007) also observed steering responses in situations with high TTC, where there was presumably enough time for the driver to plan a more controlled maneuver, but this relates less to critical collision avoidance.

Collision avoidance support systems

Finally, an important aspect of driver behavior in relation to collision accidents is driver response to warnings and interventions from in-vehicle support systems, which may hold potential for helping drivers avoid or mitigate collision accidents, for example by redirecting gaze of visually distracted drivers to the collision threat (see, for instance, J. D. Lee, McGehee, Brown, & Reyes, 2002), or by applying autonomous braking or steering of the vehicle (Itoh, Horikome, & Inagaki, 2010). A complication in this context is the phenomenon of *behavioral adaptation*, by which driver response to a support system may change over time with exposure to the system (Smiley, 2000). The driver's long-term behavior with respect to a support system, in terms of acceptance, reliance, disuse, or even misuse of the system, may depend on a multitude of factors. Examples include perceived system reliability, the degree to which the system can be understood by the driver, and the specifics of warning or intervention design (J. D. Lee & See, 2004; Meyer, 2004).

Method

Candidate scientific papers for this review were gathered using a systematic approach, from the following sources: (a) Database searches (see Appendix A for details), (b) reference lists of candidate articles, (c) researcher web pages, and (d) previous knowledge of the authors and their colleagues. Both peer-reviewed and non-peer-reviewed publications were considered.

Inclusion of candidate papers in this review was then decided based on the following criteria: (a) They should be written in *English*, and published in *the year 2000 or later*; however, some influential references of older date were also included; (b) they should describe *driver behavior models capable of controlling a simulated vehicle* laterally and/or longitudinally, using some input from a simulated traffic situation, thus excluding papers describing models of, for example, perception only or actuation only; (c) they should address traffic on *public roads*, as opposed to race track driving; and (d) they should describe simulation of *near-crash on-road collision situations*. No strict definition of what constitutes a near-crash situation (in terms of, for example, kinematics or response severity, as discussed above) was adopted, since candidate articles would rarely give information regarding such details. Therefore, application of the final inclusion criterion involved subjective judgment to some degree. In borderline cases, we have opted for inclusion rather than exclusion. However, based on this criterion, papers reporting on the use of *crash-free* traffic simulation in combination with *surrogate safety measures* (see e.g. Saka & Glassco, 2001) were consistently excluded.

Some of the driver models presented in the reviewed papers were implemented and simulated in selected scenarios; details will be provided as part of the review below. The choice of implemented models was based on an ambition to cover several different classes of models, but was also limited by the fact that many of the papers did not provide enough details to allow implementation.

Models of driver behavior in collision situations

In this section, driver models will be presented, following a rough taxonomy based on the main aspect of collision avoidance behavior addressed by the model in question. The first two subsections will be devoted to models with an emphasis on avoidance by either braking alone or steering alone, respectively. Then, models focused on the interplay of braking and steering will be covered. Thereafter, models will be described that emphasize how driver states and driver characteristics affect near-collision behavior. The last subsection will review papers in which a main topic of discussion has been the simulation platforms used for studying collision situations.

When providing model equations, a consistent notation will be used for recurring mathematical quantities, thus often departing from the exact symbols used by the original authors.

Avoidance by braking

Two main classes of deceleration-related driver models may be discerned: Those that do not take the concept of satisficing into account, and those that do. A defining characteristic of the former class is that these models will react to an obstacle at arbitrarily long distances. Below, the two classes will be reviewed separately.

Many of the models introduced below were originally proposed within the context of large-scale agent-based traffic simulations, or *microscopic simulations*, where obstacles are generally lead vehicles, and where driver models are referred to as *car-following* models (Brackstone & McDonald, 1999; Helbing, 2001).

Models assuming long-distance reactions to obstacles. A well-known longitudinal control model of this type is the car-following model by Gazis, Herman, and Rothery (1961), often referred to as the GHR model. It was not developed specifically to study collision situations, but is presented here since several more recent models, either based on the GHR model or similar to it, have been applied in such contexts. The main equation in the GHR model is:

$$\ddot{x}_F(t) = \lambda \cdot \Delta\dot{x}_{\mathrm{ff}}(t - T_R) \tag{1}$$

where $\Delta x_{\mathrm{ff}}(t) = x_L(t) - x_F(t)$, and $x_L(t)$ and $x_F(t)$ denote the positions along the road (increasing in the forward direction) of the fronts of the leading and following vehicles, respectively[2]. Dots denote differentiation with respect to time, T_R is a *time lag* (or an *apparent reaction time*), and λ is a sensitivity term defined as

$$\lambda = a\frac{\dot{x}_F^m(t)}{\Delta x_{\mathrm{ff}}^l(t - T_R)} \tag{2}$$

where a, l and m are constants.

Thus, a GHR driver aims to keep the same speed as the lead vehicle (Equation 1), and corrects for speed differences more swiftly at high speeds and low headway distances (Equation 2). Figure 2 illustrates the model's long-distance reaction in an LVS scenario (left panel), as well as the more realistic, delayed deceleration pulse-type response in an LVD scenario (right panel). Since the GHR model, in this most basic form, disregards the physical extensions of vehicles, it tends to $\Delta x_{\mathrm{ff}} = 0$ in both scenarios, corresponding to the two vehicles overlapping completely (i.e. a negative headway distance).

Over the years, much research has been devoted to the study of real traffic data in order to find the best parameter settings for the GHR model, but without conclusive results (Brackstone & McDonald, 1999; Ozaki, 1993). Sultan, Brackstone, and McDonald (2004) suggested that more realism could be obtained in scenarios involving lead vehicle accelerations and decelerations (such as LVD, but not LVS and LVM), by adding acceleration terms to Equation 1.

H. Yang and Peng (2010) instead expanded on a GHR-like model by taking into account a number of *error-inducing behaviors*, as well as *stochasticity* (unpredictability) of driver behavior, in order for crashes to be generated in their simulations. Their core longitudinal control model, derived from a large data set of driving in real traffic, can be written as

$$\begin{aligned}\ddot{x}_F(t) = P\left(\Delta x(t - T_R)\right)\Delta\dot{x}(t - T_R) + \\ C \times \left[\Delta x(t - T_R) - \dot{x}_F(t - T_R)\Delta T_d\right]\end{aligned} \tag{3}$$

where $P(\Delta x)$ is a cubic polynomial, C a constant, and ΔT_d the driver's *desired time headway*. The first term on the right hand side may be compared to Equation 1, and the cubic polynomial $P(\Delta x)$ proposed by H. Yang and Peng bears some resemblance to a $1/\Delta x$ function, corresponding to a GHR model with $m = 0$ and $l = 1$. The remaining term (proportional to C) achieves time headway control. Stochasticity was introduced by drawing acceleration values from a probability distribution around the value determined by Equation 3, with variance determined by another polynomial in distance headway. The introduced error-inducing behaviors were (a) a Weber ratio (Gray, 2010, p. 263) limiting detection of small changes in range rate; (b) eyes-off-road behavior, modeled as variations in reaction time (T_R); and (c) mind-off-road behavior, modeled as temporary increases in acceleration control variability.

In simulation, this model generated rear-end crashes at approximately twice the rate observed in accident statistics. Yang and Peng argued that this discrepancy could be due to an inability of Equation 3 to account well for highly critical collision avoidance behavior. The LVD scenario behavior shown in the right panel of Figure 2, obtained for the model as written in Equation 3, without stochasticity and error-inducing behaviors, indicates that the model comes close to avoiding the collision, but features clear oscillations in the braking response. In the LVS and LVM scenarios, this implementation of the model is unstable, due to the time headway control (not shown in the left panel of Figure 2).

Other models in this general class have been proposed by Chung, Song, Hong, and Kho (2005), who suggested a new formulation for the λ term of the GHR model, and Mehmood, Saccomanno, and Hellinga (2001), who based their model on *system dynamics* concepts. Kuge, Yamamura, Boer, Ward, and Manser (2006) parameter-fitted a model of this class to non-critical driving with and without a support system involving a haptic gas pedal, and used these two parameter settings to predict the impact of support system presence on a more critical LVD scenario.

In summary, this class of braking model has seen much application in collision avoidance contexts, and

[2] The definition of the longitudinal distance between vehicles differs between models. Most models use the distance between the front of the following vehicle and the back of the lead vehicle, denoted Δx. However, in the GHR model, the vehicles are pointlike so that, if the extension of the vehicles were to be taken into account in that model, the longitudinal distance would correspond to the front-to-front (or, equivalently, back-to-back) distance. Hence, for that model the notation Δx_{ff} is used.

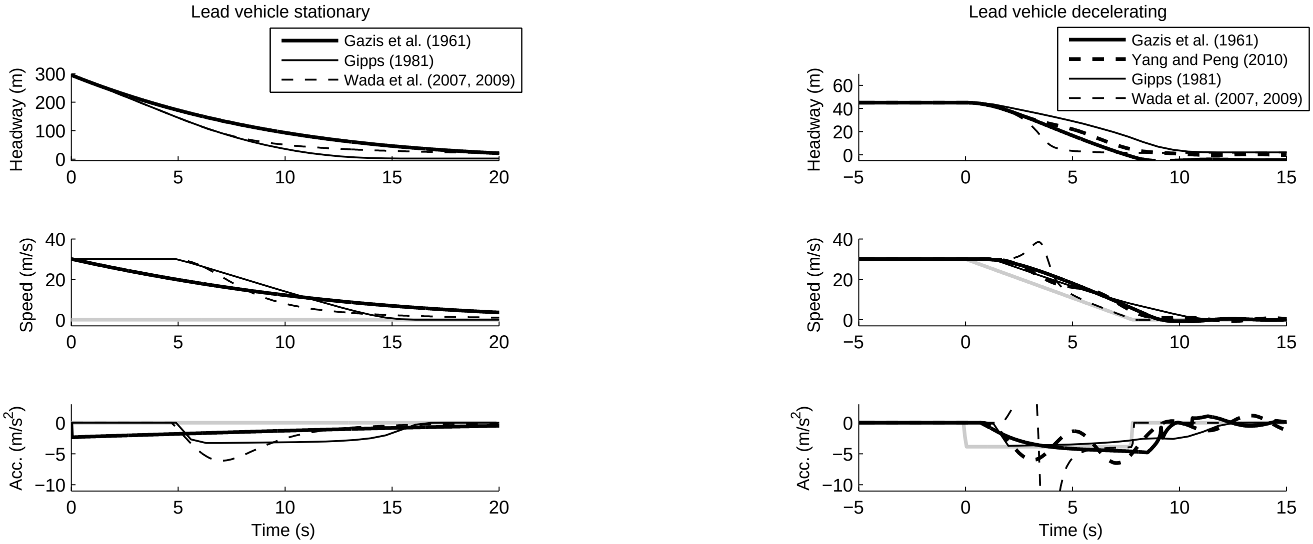

Figure 2. : Behavior of selected driver models focusing on braking. In both panels, the solid gray line shows behavior of the lead vehicle (length $l_L = 4.5m$). The left panel shows model behavior in a scenario with a stationary lead vehicle. At time $t = 20$ s, headway values were 21 m and decreasing for the Gazis et al. (1961) and Wada et al. (2007, 2009) models, and the Gipps (1981) model was stable at 2 m. The right panel shows model behavior in a lead vehicle decelerating scenario, with initial time headway of 1.5 s and constant 0.4g lead vehicle deceleration starting at time $t = 0$ s and ending at full stop. At time $t = 15$ s, headway values were -4.5 m for the Gazis et al. model, -0.4 m for the Yang and Peng (2010) model (here simulated without stochasticity and error-inducing behaviors), and 2 m for the Gipps and Wada et al. models. Parameters for the Gazis et al. model were: $T_R = 0.7$ s, $a = 1.1$, $l = 1$, and $m = 0.9$ (from Ozaki, 1993). Parameters for the Yang and Peng model were: $T_R = 0.7$ s, $C = 1$, $\Delta T_d = 1.5$ s. $P(\Delta x)$ was estimated from their Figure 3. Parameters for the Gipps and Wada et al. models were as proposed in the corresponding papers.

the work of H. Yang and Peng (2010) is especially notable. However, thorough validation on real accident data is lacking so far. Furthermore, the inherent inability of these models to generalize to less critical scenarios, where a real driver may not always initiate braking as quickly as possible, may make them less useful in applications where both normal and critical collision avoidance must be simulated.

Delayed constant deceleration models. An additional set of models, which can be considered a subclass to the one discussed above, is *delayed constant deceleration models*. Here, this term is used when referring to models of the following general type, which has seen much use in previous research:

> Starting at a (reaction) time T after a stimulus S, the driver applies a constant deceleration D.

Such a model approximates the behavior of the GHR model in the critical LVD scenario (cf. the right panel of Figure 2), and shares that model's limitations with respect to less critical situations.

The most frequent context of application for this type of model has been the study of active safety warning systems, especially forward collision warning systems. Computer simulation with such a model, with the active safety warning constituting the stimulus S, has been used for optimizing system parameter settings, and to make predictions on potential traffic safety benefits on a societal level (T. Brown et al., 2001; Fitch et al., 2008; Krishnan, Gibb, Steinfeld, & Shladover, 2001 and also Sugimoto & Sauer, 2005, although the model used in that case was slightly more advanced). Other uses of this type of model has been assessment of safety impact of in-vehicle information systems, with S being the first glance back towards the road after a lead vehicle has begun deceleration (Smith, Chang, Cohen, Foley, & Glassco, 2005), development of road geometry design guidelines, with S being the sudden appearance of an unexpected obstacle (Fambro, Fitzpatrick, & Koppa, 2000), and a study of accident causation mechanisms, with S representing the establishment of an initial collision course (Davis, 2007; Davis & Swenson, 2006). McMillan, Christiaen, and Stark (2001) also relied on this general account of collision avoidance behavior for estimating the collision probability inherent in a given empirically observed rear-end situation, but instead of defining S explicitly they varied brake initiation timing and deceleration magnitude around the empirically observed values.

Indeed, in all of the research cited above except that by Fambro et al. (2000), varying at least one of the quantities T and D was part of the approach. Often, the initial kinematics of the vehicles involved was also varied. In all cases except one (T. Brown et al., 2001), parameter variation was introduced using probability distributions, taken from previous literature or from a data set used in the corresponding research project. Another common factor in much of the abovementioned research has been the use of the driver model in analysis of recorded driving data, to answer *what if?* types of questions, such as: *what if a forward collision warning system had been present in this situation?* (Fitch et al., 2008; Sugimoto & Sauer, 2005), *what if a lead vehicle had suddenly braked during the performance of the in-vehicle secondary task?* (Smith et al., 2005), or *what if this traffic situation would have looked slightly different?* (Davis & Swenson, 2006; McMillan et al., 2001).

Although the simplicity of this type of model may rightfully raise questions of validity (for instance regarding the inability of satisficing behavior), it may nevertheless serve as an example of how also very basic quantitative driver models can be put to some use in the study of traffic safety. In some of the research cited above, the resulting overall model dynamics was even tractable analytically, so that actual simulation was not needed (Davis, 2007; Fambro et al., 2000; Krishnan et al., 2001; McMillan et al., 2001).

Models assuming timed brake application. A satisficing driver approaching an obstacle may be assumed to exhibit a safety margin-related, timed transition from a non-decelerating state to a decelerating state. Longitudinal driver models have been proposed that try to capture such a phenomenon. In the much cited model by Gipps (1981), the mode transition in LVS, LVM, and LVD scenarios, as exemplified in Figures 2 (left panel) and 3, occurs when the vehicle speed prescribed by the equation

$$\dot{x}_F(t) = b_F T_R + \Big[b_F^2 T_R^2 - b_F \Big(2[\Delta x(t - T_R) - s_L] - \dot{x}_F(t - T_R) T_R - \frac{\dot{x}_L(t - T_R)^2}{b_L} \Big) \Big]^{1/2} \quad (4)$$

falls below the initial cruising speed of the following vehicle. This equation, as written above, is difficult to interpret, but the assumption from which it is derived, using basic Newtonian mechanics, is clear: The following vehicle driver is assumed to adjust speed to a value such that, if the lead vehicle should suddenly brake with an assumed maximum deceleration $b_L < 0$, the following vehicle driver will be able to avoid a collision without exceeding the own preferred maximum deceleration b_F, as long as the actual reaction time does not exceed a *safety reaction time* $1.5T_R$. s_L is the *effective size* of the lead vehicle, "the physical length plus a margin into which the following vehicle is not willing to intrude" (Gipps, 1981, p. 106). It may be noted that, in contrast to the GHR model, which predicts vehicle *acceleration* at each time step, the Gipps model operates directly on the vehicle *speed*. Gipps demonstrated, however, that in his model the effective deceleration in a simulation time step will never exceed b_F.

Figure 2 shows that in an LVD scenario, the Gipps model replicates the delayed constant deceleration type of behavior already seen for non-satisficing models, but manages to avoid the collision and to stop in a controlled manner. In an LVS scenario, the model generates a clearly identifiable, timed brake initiation. Interestingly, Figure 3 indicates that inverse TTC at brake initiation, as predicted by the Gipps model, exhibits a similar dependence on following vehicle speed as that observed by Kiefer et al. (2005) in their test track data, although with a different effect of lead vehicle speed (higher values of inverse TTC for LVS than for LVM, rather than the other way around). Further support for the Gipps model was provided by K. Lee and Peng (2004), in their benchmark comparison of car-following models measuring model performance when fitting normal driving and non-critical approach sequences. K. Lee and Peng (2004) and Peng (2002) also proposed a slight modification to the Gipps model that, however, does not seem to have a large impact on the types of scenarios studied here.

In its original formulation, the Gipps model will never lead to actual crashes in simulation, which is clearly a limitation in the study of near-crash and crash events. However, as in the case of the GHR model, some researchers have adapted the Gipps model to study accident situations. A crash-inclusive variation to the model was proposed by Hamdar and Mahmassani (2005), with the aim of mimicking driver behavior in traffic situations of general panic (e.g. during evacuations due to natural disasters or similar events). Another variation, aimed at driving in more normal traffic conditions, was proposed by Xin, Hourdos, Michalopoulos, and Davis (2008). Their approach was based on complementing the basic Gipps model with a number of insights from psychology (not dissimilar to what H. Yang & Peng, 2010 did with their GHR-like model). A *visual scanning interval*, mimicking a divided attention to driving, was introduced, and at each scan a new target speed according to Equation 4 would only be set if changes in relative position or motion exceeded perceptual thresholds (Weber ratios), or if the lead vehicle deviated from a desired time headway ΔT_d by more than a certain fraction (headway satisficing). It was demonstrated that the model could be parameter-fitted to sequences of real driving from both a data set of normal, non-critical traffic, and a data set of six crashes and four near-crashes, involving a total of 54 vehicles on a high crash-rate section of a US freeway.

Another general means of introducing satisficing in a behavior model is to include concepts from *fuzzy logic* (Zadeh, 1965), where *fuzzy states* are typically defined as intervals for involved state variables, and control actions may be modeled as occurring only once deviation from a non-action state becomes large enough. Steigerwald (2002) carried out a simulation study of the safety effects of collision warning systems, using the fuzzy logic car-following model of McDonald, Wu, and Brackstone (1997). This model was driven by *fuzzy rules* such as, for example *if distance divergence is Too Far and relative speed is Closing* then the driver's response is *No Action (keep current speed)*. Steigerwald observed crashes in his simulations, and found reductions in crash rate when driver response to collision warnings was included, modeled as a decreased reaction time setting in the car-following model.

Finally, the following quantity, which has been used in two separate models of braking behavior, will be considered:

$$K_{dB} = \begin{cases} 10\log_{10}(K)\,\mathrm{sign}(-\Delta\dot{x}) & \text{if } K \geq 1 \\ 0 & \text{if } 0 \leq K < 1 \end{cases} \quad (5)$$

where $K = \left|4 \cdot 10^7 \cdot \Delta\dot{x}/\Delta x^3\right|$ km h^{-1}m^{-3} (note the non-SI unit, used by the original authors, for relative speed). This quantity was defined by Wada, Imai, Tsuru, Isaji, and Kaneko (2007), based on a retinally oriented account reminiscent of that of D. Lee (1976). When a collision course is established, K_{dB} will rise from zero, and will reach higher values as the vehicle approaches collision. Wada, Imai, et al. (2007) found that in less critical situations, driver control of deceleration could be well described as a strategy in which $\mathrm{d}K_{dB}/\mathrm{d}\Delta x$ is held constant. Furthermore, they found that brake initiation timing could be modeled as occurring once a lead vehicle speed dependent variant of K_{dB} surpassed a threshold (Wada, Doi, et al., 2007; Wada, Hiraoka, & Doi, 2009). Figure 3 indicates that this brake initiation model is qualitatively similar to what the Kiefer et al. (2005) and Gipps (1981) models predict, although with no visible difference between LVM and LVS. In an LVS scenario the behavior of the model by Wada, Imai, et al. (2007) and Wada et al. (2009) is also qualitatively similar to that given by the Gipps model (Figure 2, left panel), but with stronger and more brief deceleration, whereas the right panel of Figure 2 suggests that a strategy in which $\mathrm{d}K_{dB}/\mathrm{d}\Delta x$ is kept constant is not realistic in the more critical LVD scenario, as indicated by the authors themselves.

Akita, Inagaki, Suzuki, Hayakawa, and Tsuchida (2007) incorporated the K_{dB} quantity in their *piecewise linear auto-regressive exogenous inputs* (PWARX) model of driver speed keeping. By use of clustering algorithms on data in the $(K_{dB}, \Delta\dot{x}, \Delta x)$ space from a small simulator study ($n = 2$), four speed keeping *modes*, of which one was *collision avoidance*, were identified and separated. For each of these modes, a separate ARX model, each on the form:

$$p(k+1) = aK_{dB}(k) + b\Delta\dot{x}(k) + c\Delta x(k) + dp(k) \quad (6)$$

was fitted to the data. In this equation, k denotes simulation time step, p is the pedal input, and a, b, c, and d are driver-dependent constants. Judging by the figures provided by Akita et al. (2007), it however seems as if braking events in their dataset were sparse, and possibly not highly critical.

In summary, this class of braking model may be more generally applicable than other models, since it is able to exhibit satisficing behavior in less critical scenarios, such as LVS and LVM. Figure 3 points to a possible convergence in this respect between some of the models. Furthermore, the simulated behavior of the Gipps (1981) model seems more stable than the simulated non-satisficing models. Whereas validation on real accident data is generally missing also for this model class, Xin, Hourdos, Michalopoulos, and Davis (2008) have provided a commendable exception. Further details on their work, including calibrated values

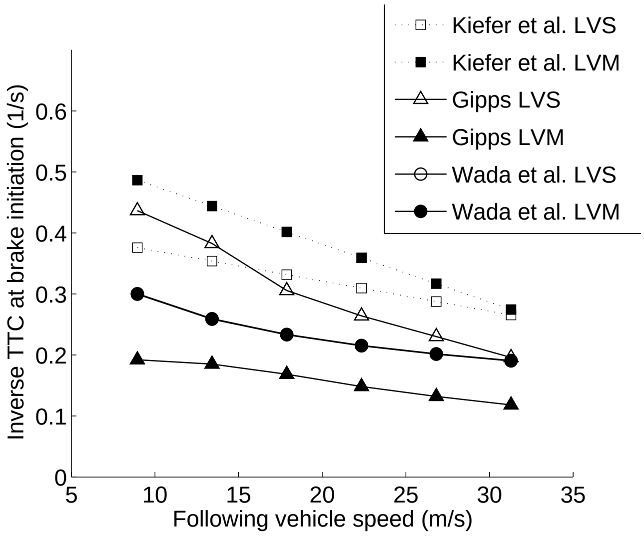

Figure 3. : Inverse time to collision at brake initiation, as a function of following vehicle speed, in the lead vehicle stationary (LVS) and lead vehicle moving (LVM) scenarios, for the Gipps (1981) and Wada et al. (2009, Equation 9) models, respectively, as compared to the results of Kiefer et al. (2005). In both simulated scenarios, the initial following vehicle speed was 30 m/s, and in the LVM scenario the lead vehicle speed was 15 m/s. The two curves for the Wada et al. model are not identical, but are close enough to appear overlapping in this figure.

for model parameters, can be found in (Xin, Hourdos, & Michalopoulos, 2008).

Avoidance by steering

Few driver models are specifically designed for collision avoidance by steering. However, many models of steering have been benchmarked on rapid evasive maneuvers that mimic collision avoidance situations, such as the ISO double lane change (ISO, 1999). Here, the main objective has typically not been to create models that accurately replicate human behavior in accident situations. Rather, research has been more focused on finding models that *perform well* in terms of path tracking and stabilization. Nevertheless, since detailed steering models are important in some collision-related application contexts, all identified steering models tested on rapid evasive maneuvers have been included in this review, and their control performance will be reported below. A later section will then describe how some models have been tuned for sub-optimal performance, to account for inter-driver behavior variability in collision avoidance.

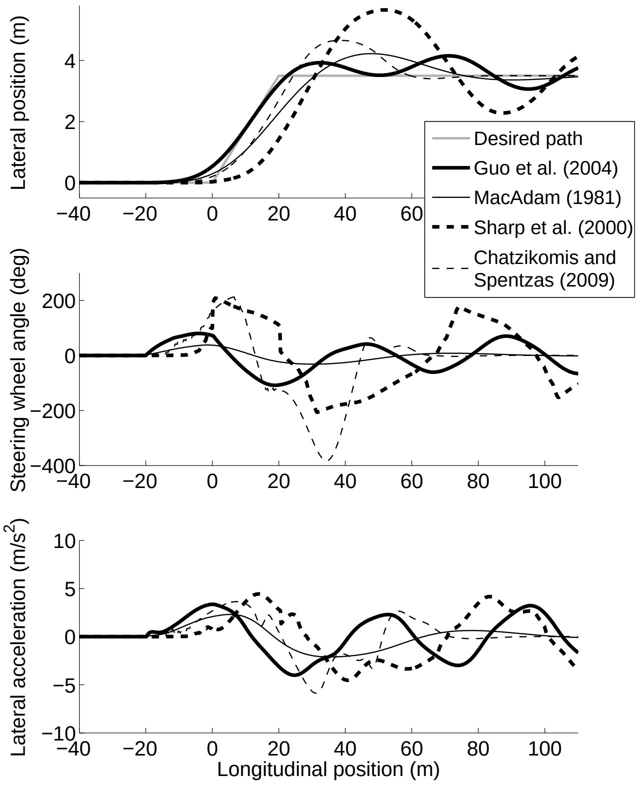

Figure 4. : Steering behavior of selected driver models carrying out a 20 m single lane change, at 20 m/s. Parameters for the models were chosen as proposed in the corresponding papers. Among the parameter sets proposed by MacAdam (2001), the following was adopted: A preview time of 1.3 s, a response delay of 0.2 s, and 10 preview points.

Traditionally, driver models with steering capabilities have been based on classical control theory (Jürgensohn, 2007). Even though other types of models have been developed recently, most of the steering models are still based on, or contain elements from, control theory. Typically, the input to such models is a *desired path* containing the desired lateral road position over time. In order to correct deviations from this desired path, the steering models output one of the following quantities: (a) The steering wheel angle, (b) the vehicle steering angle, or (c) the lateral acceleration.

When simulating models that operate on steering angles rather than directly on lateral acceleration, a vehicle model must be incorporated in the simulation. For our simulations (see Figure 4) we used the simulation environment of Benderius, Markkula, Wolff, and Wahde (2011), and implemented the vehicle dynamics model of Thommyppillai, Evangelou, and Sharp (2009), with parameters as specified in Appendix B.

Models using path preview. In order to predict deviations before they occur, driver models often use *path preview*. The simplest form is *single point preview*, where the expected deviation in, for instance, lateral position or heading angle is measured at a single point located a distance S_p in front of the vehicle. The distance S_p is often defined as a function of a constant *preview time* T_p as

$$S_p(t) = \dot{x}(t)T_p \tag{7}$$

where $\dot{x}(t)$ is the longitudinal speed of the vehicle.

Reński (2001) and M. Lin, Popov, and McWilliam (2003) independently of each other proposed two similar single point preview models, in which the vehicle steering angle $\delta(t)$ is given by

$$\delta(t) = K\epsilon(t - T_R) \tag{8}$$

where $\epsilon(t)$ is the angle between the heading of the vehicle and the preview point, T_R the driver reaction time, and K a gain constant[3]. Both Reński and M. Lin et al. showed that this driver model was capable of carrying out a double lane change maneuver, and studied model behavior for varying parameter settings. Furthermore, Reński optimized model parameters to reproduce the recorded trajectory of a real driver.

Guo, Ding, Zhang, Lu, and Wang (2004) also used single point preview in their *preview-follower model*, originally proposed by Guo and Fancher (1983). Within this model, the current acceleration, velocity, and position of the vehicle are used in order to predict the lateral error at time $t + T_p$. Then, the steering wheel angle required to correct this previewed error is calculated, assuming a simple vehicle model. Guo et al. (2004) compared data from a simulator study where drivers carried out a double lane change maneuver, with model output for a preview time of 1.4 s, and found good agreement. The same model was used in a double lane change also by Gao, Zheng, Guan, and Guo (2002). Figure 4 suggests that when parameterized as proposed by Guo et al. (2004), this model can manage a rapid single lane change very well, although with some problems regaining stability afterwards.

Based on the preview-follower model, Zhuang, Yu, and Li (2005) applied an artificial neural network in order to calculate optimal preview times for a variety of different test tracks at different vehicle speeds. It was found that optimal preview times (for the model used) were in the range from 1.1 to 1.3 s, and that higher speeds required slightly longer preview times (suggesting that Equation 7 should, in fact, be somewhat nonlinear).

Overall, it may be noted at this point that the use of a desired path in combination with some form of path preview may raise questions regarding model validity in real collision situations. One could argue that this type of preview, as well as some of the even more advanced control theory practices reviewed below, imply that the modeled driver plans ahead in a more controlled fashion than what may be the case in accident situations. Alternative standpoints are also possible, however, and the topic will be considered further in the discussion.

Multi-level models. Donges (1978) provided the first example of another class of driver models, the *two-level driver models*, which typically include path preview as discussed above. The two levels are called *anticipation* and *stabilization* (the latter also *compensation* or *guiding*). At the anticipation level, steering is estimated in an open-loop manner based on the curvature of the previewed desired path and a simplified vehicle dynamics model. The vehicle model is referred to as the *internal vehicle model*, representing the driver's understanding of the vehicle. Deviations from the desired path can, for instance, occur as a result of system noise or simplifications in the internal vehicle model. At the stabilization level, the model compensates for such deviations in a closed-loop manner.

A recent two-level model was introduced by Edelmann, Plöchl, Reinalter, and Tieber (2007). In this model, a nonlinear vehicle dynamics model is locally linearized and used at the anticipation level. By using two preview points in front of the vehicle (in order to anticipate changes in curvature) a steering wheel angle estimate can be calculated.

Plöchl and Lugner (2000) introduced a *three-level driver model*. If large local path deviations occur, the third level can temporarily override anticipation and stabilization in order to steer towards the desired path as quickly as possible without using path preview. This approach is interesting especially in relation to the potential concerns raised above, regarding the use of preview in models of critical collision avoidance.

[3] It may be noted, however, that M. Lin et al. (2003) themselves referred to their model as a two-level model, as discussed in the next section.

Models using optimization over a preview horizon. Another class of model determines a steering response by optimizing over a *preview horizon* (also referred to as the *preview interval*). This relates to the control theory concept of *optimal control* (see e.g. Kleinman, Baron, & Levison, 1970; Vinter, 2010). Here, the term *optimal* does not imply that these models cannot exhibit satisficing behavior. Optimization criteria can be defined so as to manage a trade-off between, for example, path deviation and steering effort, which would typically be referred to as satisficing.

An early driver model optimizing over a preview horizon was introduced by MacAdam (1981). The model determines, in each time step, the vehicle steering angle that minimizes a path deviation cost function over the preview horizon. The top panel of Figure 4 shows good tracking performance for this model, even with comparably small steering wheel inputs (middle panel). In a later version of this model (MacAdam, 2001, 2003), the original linear internal vehicle model was replaced by a non-linear one, improving the performance of the driver model in situations close to the limits of the vehicle's capabilities. The extended model also offers the possibility to have the preview time varying in magnitude depending on upcoming road geometry. When using this feature in a double lane change, the preview time was shown to vary within a range from 0.6 to 2.0 s.

Peng (2002) developed a driver model that extends MacAdam's original model (1981) with a more general cost function, as well as the capability of updating the internal vehicle model during operation, something that is often referred to as *vehicle adaptation*. These extensions were later shown to improve control performance in a double lane change maneuver Ungoren and Peng (2005).

Prokop (2001) and Butz and von Stryk (2005) proposed models with a variety of terms in their cost functions, including satisficing-related terms aimed at limiting lateral accelerations. These two models differ from the other reviewed optimal control models in that they are two-level models, first determining a desired path by optimization over the preview interval, and then applying stabilization control to follow the optimized trajectories. Butz and von Stryk provided examples of their model's behavior in a double lane change maneuver, for a number of different weightings of their optimization criteria. A similar model can also be found in (Vögel, von Stryk, Bulirsch, Wolter, & Chucholowski, 2003).

Yoshida, Shinohara, and Nagai (2008) employed an optimization method similar to the one used by MacAdam to derive open-loop steering interventions for use in an active safety system, aimed at achieving automatic collision avoidance.

Models using multi-point preview. Models optimizing over a preview horizon show good stabilization capabilities in relation to rapid maneuvers (see e.g. Figure 4). However, optimizing over a interval may, depending on sampling rate and optimization method, be computationally intensive. An alternative approach is to use *multi-point preview*, in which the driver model uses a discrete number of points in front of the vehicle for its tracking behavior. Typically, the points are individually weighted and positioned at fixed preview times.

The model by Sharp, Casanova, and Symonds (2000) uses a multi-point preview control scheme, where points are positioned at fixed preview times in front of the vehicle. The vehicle steering angle $\delta(t)$ is given by

$$\delta(t) = K_\psi \psi_e(t) + K_1 y_{e_1}(t) + \sum_{i=2}^{n} K_i y_{e_i}(t) \tag{9}$$

where $\psi_e(t)$ is the heading error compared to the tangent of the desired path, $y_{e_1}(t)$ the vehicle's lateral deviation, $y_{e_i}(t)$ the lateral deviation of the preview points, and K_ψ, K_1, and K_i are gain constants. The model was originally intended for race track applications, but was used by Wenzel, Burnham, Williams, and Blundell (2005) for studying the utility of a stability support system in a double lane change maneuver. The large overshoot seen in our simulations (Figure 4) is probably due to the fact that Sharp's parameterization is tuned for race car dynamics.

In the multi-point model by Thommyppillai et al. (2009) a non-linear vehicle model is linearized for different values of the vehicle speed and the front axle slip ratio. An *adaptive control strategy*, where control gains are derived depending on vehicle properties, is then determined by using the linearized vehicle model. In the same paper, the authors compared the adaptive control strategy with a fixed gain strategy, and found that the model with adaptive gains showed significantly better tracking performance.

Another multi-point driver model, which has been used in a double lane change, was proposed by Chatzikomis and Spentzas (2009). The model uses a combination of two error measures: (a) Errors in heading angle, and (b) errors in lateral position. A vehicle steering angle is then calculated using a weighted sum of both errors, and an adaptive control strategy based on longitudinal speed. By determining error weights using stochastic optimization, Chatzikomis and Spentzas found that, for their model, heading angle errors were a more important input than lateral position errors. Figure 4 indicates that this model achieves good tracking performance, despite large steering magnitudes.

Other models of steering. Some models will now be described that do not fit into the model classes outlined above. Gao and Jiang (2009) proposed a model in which *path planning* is implemented. At any instant in time, all feasible trajectories are determined based on the current vehicle state, steering limit, and lane boundaries. The best trajectory is then chosen according to a safety index, based on the distance to the center line, and a maneuverability index, based on the required change in the lateral acceleration.

A piecewise polynomial steering model intended for obstacle avoidance was proposed by Kim et al. (2005). The model consists of four modes, each modeled in the form

$$\delta_{SW}(t) = a\Delta x(t) + b\Delta \dot{x}(t) + c\Delta y(t) \quad \text{if } d \leq \Delta x(t) < e \tag{10}$$

where $\delta_{SW}(t)$ is the steering wheel angle, and $\Delta x(t)$ and $\Delta y(t)$ the longitudinal and lateral distances, measured relative to the obstacle. The parameters a, b, c, d, and e are constants which Kim et al. determined from driving data. Each mode represents a specific steering behavior that is activated depending on the longitudinal distance to the obstacle; see Equation 6 for a similar model of driver braking behavior.

A driver model based on a neural network was proposed by Y. Lin, Tang, Zhang, and Yu (2005). The model has two outputs, steering wheel angle and steering wheel rate, and uses seven inputs, one of which is the lateral displacement from the desired path, another is the lateral displacement of a preview point, and the rest are vehicle state properties. Y. Lin et al. (2005) tested the model, by first training the network on driving data, in various steering maneuvers.

A steering model that differs from the models previously discussed in this section, in the sense that it models a purely open-loop response, was introduced by Araszewski, Toor, Overgaard, and Johal (2002). It was developed for the reconstruction of single lane change maneuvers in accident situations. For a given vehicle speed and given longitudinal and lateral lane change distances it generates a *sine or triangle wave* steering wheel response. The authors did not report on any use or validation of the model in reconstruction of actual accidents.

Avoidance by a combination of braking and steering

In several of the papers cited in the previous section (e.g. Butz & von Stryk, 2005; Chatzikomis & Spentzas, 2009; Guo et al., 2004; MacAdam, 2001; Prokop, 2001), models of braking were also proposed in order to adjust speed in normal driving conditions, for example in curve negotiation. This section will focus specifically on models that have been used for simulating the combined use of braking and steering in collision avoidance.

The driver model proposed by Jurecki and Stańczyk (2009) is capable of both steering and braking, and was designed specifically for collision avoidance at intersections. The braking of the model is defined as

$$a_b(t) + K_1 \dot{a}_b(t) = K_2 \Delta y(t - T_{R_b}) + K_3 \frac{\Delta \dot{x}(t)}{\Delta x(t)} \tag{11}$$

where $a_b(t)$ is the vehicle deceleration, $\Delta x(t)$ and $\Delta y(t)$ the longitudinal and lateral distances to the conflicting car (driving in a direction perpendicular to the modeled driver's vehicle), T_{R_b} the braking reaction time, and K_1, K_2, and K_3 are constants. The steering of the model is defined as

$$\delta(t) + K_4 \dot{\delta}(t) = K_5 \Delta y(t - T_{R_s}) \tag{12}$$

where $\delta(t)$ is the vehicle steering angle, T_{R_s} the steering reaction time, and K_4 and K_5 are constants. In order to find suitable values for the model constants, Jurecki and Stańczyk used driving data acquired from a test track experiment.

By conducting an experiment where subjects were asked to drive around a test track, Yamakado and Abe (2008) found a relation between lateral (steering) and longitudinal (braking) accelerations during driving. They defined this relation, in the Laplace frequency domain (frequency variable s), as

$$a_x(s) = -\text{sign}(a_y(s)\dot{a}_y(s)) \frac{K \dot{a}_y(s)}{1 + T_d s} + a_{x_0}(s) \tag{13}$$

where $a_x(s)$ is the longitudinal acceleration, $a_y(s)$ the lateral acceleration, K a gain constant, T_d a delay time, and $a_{x_0}(s)$ a model input denoting the working point of the longitudinal acceleration. In practice, this means that longitudinal acceleration will, with a delay determined by T_d, tend to (a) a_{x_0}, if lateral acceleration is constant; (b) a more negative value than a_{x_0}, if lateral acceleration is increasing (to either left or right); or (c) a more positive value than a_{x_0}, if lateral acceleration is decreasing. Yamakado and Abe complemented this model with the preview-follower model of Guo et al. (2004), and found good agreement between their simulations and single lane change data from a test track.

In another class of driver models, generally exhibiting satisficing behavior, control inputs are calculated based on road or obstacle boundaries rather than (as for the steering models discussed so far) on a desired path (predefined or optimized). For instance, Gordon and Magnuski (2006) introduced a driver model that, by treating all navigation as collision avoidance, is capable of both braking and steering. According to the current state of the vehicle dynamics, the model estimates the point where the vehicle would cross the lane boundary. By applying appropriate control input, the driver shifts the estimated crossing point further down the road. Similar models, based on fuzzy logic, navigate as a result of always trying to keep lane boundary distances within safe margins (El Hajjaji & Ouladsine, 2001; Zeyada, El-Beheiry, El-Arabi, & Karnopp, 2000). Zeyada et al. showed that their relatively simple model manages both to negotiate a sharp turn, and to avoid an obstacle.

Gordon and Best (2006) introduced another model that does not require a desired path. Based on road geometry, a velocity vector field is determined for the drivable area. At each point in the vector field, the desired velocity, acceleration, heading, and yaw rate are determined. The steering angle and the deceleration are then derived using simple control strategies.

Sugimoto and Sauer (2005) carried out *what-if* simulations of reconstructed rear-end accidents to estimate the potential benefit of a collision avoidance support system. Their driver model responded to collision warnings either by open-loop evasive steering behavior(implemented as one period of a sine wave), by an open-loop evasive braking behavior (implemented as a delayed constant deceleration), or by a combination of the two. However, although the simulated scenarios were based on actual accidents, the authors provided only limited empirical support for the driver model itself.

Effects of driver states and characteristics

Next, models will be discussed that emphasize variability in near-collision behavior, due to (a) visual distraction, (b) driving skill and style, and (c) other driver states and characteristics.

Effects of visual distraction. Several researchers have put modeling emphasis on the collision-related effects of glances directed away from the forward roadway, e.g. to mirrors or in-vehicle displays. Two phenomena which have been recurrently addressed in this context are (a) visual allocation strategies, determining how a driver will control eyes on/off road behavior; and (b) off-road glances delaying driver reactions to a potential forward collision threat at least until gaze is again on the road ahead.

Smith et al. (2005), studied the safety effects of in-vehicle information systems, by replaying in simulation actual recorded vehicle following sequences, including on/off road glance data. Thus, in this case, there was no need for a separate model of visual allocation, only the stimulus-reaction type braking response previously discussed in the section on delayed constant deceleration models.

Delorme and Song (2001) proposed a model of driver behavior for use in traffic microsimulation. The model was based on structuring the driving task into separate driving schemata, such as *following* and *overtaking*. In the context of this review, the main importance of this model was the proposed approach of relating the occurrence of speedometer glances and side glances to the currently active driving schema, and the use of externally scripted commands to trigger glances relating to in-vehicle secondary tasks. Deceleration and braking behavior, available when gaze was on-road, was then triggered by TTC thresholds and was implemented as linear control of range and range rate. No validation or calibration on critical driving situations was provided, however.

In the *attention-based rear-end collision avoidance model* (ARCAM) of T. Brown, Lee, and McGehee (2000), visual allocation was driven by an *uncertainty* regarding the *collision potential* with respect to a lead vehicle. In ARCAM, uncertainty increases as a function of time during off-road glances, and on-road glances are triggered when uncertainty reaches a threshold level. Deceleration in response to collision situations is then delayed by an expectancy-dependent reaction time, and deceleration magnitude is set as a function of the collision potential quantity, in closed-loop control (not defined in detail by the authors). ARCAM was validated to some extent on simulator data, by T. L. Brown, Lee, and McGehee (2001), and was put to practical use by J. D. Lee et al. (2002). They used the model to extrapolate from data found in a simulator study on visual distraction and collision warnings, thus demonstrating a potential benefit of computer simulation as a complement to tests with real drivers in the loop.

Effects of driving skill and driving style. Some authors have studied how to adapt driver behavior models to represent varying levels of driver skill, as well as different driving styles. This has been done, for example, in the context of simulation-based estimation of vehicle handling properties (Data, Pascali, & Santi, 2002), and to support arguments on how to adapt the dynamics of an articulated vehicle to suit different driver skill levels (X. Yang, Rakheja, & Stiharu, 2001).

All of the reviewed models in this group have been control-theoretic models of avoidance by steering, similar to those discussed earlier in this paper, and all have been applied to double lane change maneuvers: X. Yang et al. (2001) used a single-point preview model, extended with provisions for stabilization of truck-trailer articulation. Data et al. (2002) used a two-level model. The model of Noh, Jung, Choi, and Yi (2007) performed optimization over a preview horizon. Erséus (2010) adopted the high-level architecture of MacAdam (2003), but proposed new formulations for the individual sub-modules. Irmscher and Ehmann (2004) used the driver component of a commercial simulation environment, but did not describe the driver model in full detail [4].

Among these authors, only Data et al. (2002) did not discuss any specific dimensions of driving skill or style. They varied the preview time and control gain parameters of their model, resulting in variations in steering wheel behavior that were qualitatively similar to what had been observed for three drivers on a test track.

The other authors listed above have all addressed driving skill in the parameterizations of their models. The strongest common denominator has been the treatment of the preview time parameter, which has consistently been set to higher values when representing more skilled drivers. In the case of X. Yang et al. (2001), this was also complemented with a lower control gain setting. Furthermore, all of these authors have modeled less skilled drivers as having slower and more inexact steering responses, although achieved in slightly different ways by different authors. Erséus (2010) and Irmscher and Ehmann (2004) also increased the accuracy of the internal vehicle model as a function of increasing skill. In terms of validation, Noh et al. (2007) and Erséus (2010) were alone in comparing their results with real driving data, from a test track and a driving simulator, respectively.

Additionally, Irmscher and Ehmann (2004) varied model parameters to capture behavior of aggressive drivers. These were hypothesized to over-estimate the cornering abilities of their vehicle, and to use shorter preview distances and less smooth desired paths. The combination of low skill and high aggressivity was shown to result in a driver model that was prone to control loss in the double lane change maneuver.

Effects of other driver states and characteristics. In addition to the aspects considered above, several other driver states and characteristics have been modeled and simulated in the context of collision avoidance. Some of these contributions come from Salvucci and colleagues, who use the cognitive architecture ACT-R (atomic component of thought-rational) to model driver behavior in general (Salvucci, 2006). ACT-R is modular, and at its core are a number of buffers, written to and read from by the various modules and by central IF-THEN type *production rules*, firing in series at frequencies up to a maximum rate (typically one production rule every 50 ms), thus acting as a central bottleneck for cognition. This cognitive architecture has been used to model and reproduce a large number of experimental results (Anderson & Lebiere, 1998).

In two related papers, Salvucci (2002) and Salvucci and Taatgen (2008) extended the ACT-R driver model to account for cognitive distraction due to a secondary task where several words needed to be kept in memory. In these contributions, both the primary driving task and the secondary cognitive task were modeled as requiring repeated firing of production rules in a central processing resource. Since these production rules fired serially, performance of the cognitive secondary task resulted in a general slow-down of driving-related processing in the model, which caused increases in reaction times to safety-critical lead vehicle braking events, as observed in a driving simulator experiment.

Salvucci, Chavez, and Lee (2004) modified the ACT-R model of driving in order to study effects of old age on brake response, in a situation with risk of stop light violation, but without intersecting traffic (thus making the model a borderline case for inclusion in this review). Based on previous work on ACT-R and aging, they introduced a 13% slow-down of production rule firing rate, and were thus able to reproduce an interaction effect observed in a test track experiment: When driving with a visual-manual secondary task, brake reaction times of both young (25-36 years) and old (>55 years) drivers increased, but the increase was significantly greater for the older drivers.

[4] Also MacAdam (2001), Prokop (2001), and Ungoren and Peng (2005) discussed, to some extent, how to parameterize their steering models to account for effects of driving skill and style, but put less emphasis on this issue.

A similar slow-down due to old age was introduced by B. Wang et al. (2002), in a control theoretic model due to Allen (1982), controlling lane position and heading to follow a predefined desired path. B. Wang et al. studied the behavior of this model for values of its neuromuscular delay parameter corresponding to simple task reaction times reported in the experimental literature (around 0.30 s and 0.45 s, for young and old drivers, respectively, i.e. an increase of 50% with age). They also varied the amount of derivative control of the model, citing previous researchers who found such control to be less pronounced in older drivers. Their simulations predicted that aged drivers should perform worse (deviate more from the desired path, use wider steering movements, or a combination thereof) during a single lane change, especially on a low friction road surface, and that they would benefit from a proposed four-wheel steering control algorithm. These predictions were not validated on any actual driving data, however.

Age-related slowing of reaction time (by 20%) was also included in the driver-vehicle simulation model by Delaigue and Eskandarian (2004), aimed at predicting total stopping distances of passenger cars in emergency braking. Based on previous literature, they proposed a non-driver-specific model of braking foot movement, triggered by a braking stimulus, but with a driver-specific reaction time delay. Expressions were provided for the mean and variance of this delay, as a function of driver age, driver gender, and degree of expectancy of the stimulus. However, the driver parts of their model were not subject to any validation.

Simulation platforms

A number of researchers have proposed entire platforms for simulation of traffic with collisions (Furukawa, Seki, & Fujikawa, 2009; Kitaoka et al., 2009; Wood, Dumbuya, Zhao, Hill, & Thomas, 2003; Yuhara & Tajima, 2006). This is reminiscent of the high-level perspective adopted in the previously mentioned field of microscopic traffic simulation, although the driver models reviewed here differ markedly from the car-following models typically used in that field (see Brackstone & McDonald, 1999; Helbing, 2001). None of the reviewed papers provided full specifications of the driver models, but strong common denominators can nevertheless be discerned, especially in terms of the adopted general model architectures, which are clearly inspired by information processing concepts (Wickens & Hollands, 2000). In a first step, the proposed driver models perceive the traffic surroundings, and build a mental representation of it. Then, based on this representation, rule-based decisions on actions are made, and finally the actions are carried out, in terms of vehicle operation and control.

A majority of the models (Furukawa et al., 2009; Kitaoka et al., 2009; Yuhara & Tajima, 2006) include explicit, probabilistic mechanisms for error generation, at all three stages of processing outlined above. The errors are introduced in order to have simulations generate accidents, with the purpose of estimating safety impacts of various active safety systems. Kitaoka et al. (2009) and Yuhara and Tajima (2006) also included basic on/off road visual distraction behavior. Wood et al. (2003) did not include any explicit accident causation mechanisms, but instead manually tuned decision-making of their driver models to reproduce a specific head-on collision event from real traffic.

Furthermore, Kitaoka et al. (2009) put a stronger emphasis than the others on driver characteristics and states, and Yuhara and Tajima (2006) were alone in including a specific evasive maneuvering mode, triggered by a TTC criterion. However, thorough validation on accident-related data from real traffic seems to be lacking for all models.

Garcia, Libreros, and Contreras (2008) proposed an infrastructure-oriented simulation platform, aimed at predicting risk of accidents due to visibility problems at skewed intersections.

Discussion

The discussion below will focus on three topics, namely (a) how to choose models for use in future applications, (b) potential areas for future model development, and (c) issues related to model validation and comparison. Some concluding remarks will also be made.

Putting the reviewed models to use

The reviewed papers show a wide range of applications of driver models in computer simulation. Notable examples of methodologies include the use of simulation for (a) identification of preferable designs for vehicles or infrastructure (see e.g. T. Brown et al., 2001; Garcia et al., 2008; B. Wang et al., 2002); (b) analysis of naturalistic driving data, for example to answer *what-if?* questions (see e.g. Davis & Swenson, 2006; Fitch et al., 2008); (c) interpolation within, or extrapolation beyond, a limited data set of human driving (see e.g. Kuge et al., 2006; J. D. Lee et al., 2002); and (d) reconstruction of accidents (Araszewski et al., 2002; Sugimoto & Sauer, 2005).

Other authors have focused less on specific applications, but have instead used their driver models to formalize and test hypotheses on underlying psychological mechanisms (Salvucci & Taatgen, 2008; Salvucci et al., 2004; possibly also e.g. Wada, Doi, et al., 2007; H. Yang & Peng, 2010; Xin, Hourdos, Michalopoulos, & Davis, 2008). In other words, it seems that driver models may be of value in applications, both directly as components in simulation tools to be used by vehicle or infrastructure designers, and indirectly as components in research methodologies providing scientific knowledge that can shape guidelines for design.

Overall, it is clear that a wealth of different driver models has been proposed, with models of widely varying forms and modeling paradigms, from the simplest linear control laws to full cognitive architectures. For the researcher aiming to use or extend an existing driver model, the choice of one model from this seemingly fragmented field of research is not a trivial one, and no straightforward general recommendations can be provided here. It seems likely that the high complexity of driver behavior will continue to force researchers to limit their modeling scope so as to fit the specific application at hand, just as it has for the authors of the reviewed papers.

As an illustrative and important example, it may be noted that different authors have had to consider different application-specific requirements regarding which parts of the pre-crash timeline (Fig. 1) to cover. Many researchers have mainly been interested in the details of control in near-crash and crash phases, and have thus not needed to provide any account of *why* these states were reached in the first place (see e.g. Delaigue & Eskandarian, 2004; Jurecki & Stańczyk, 2009, and the large body of work on avoidance by steering). Other researchers have included in their scope also the low risk and conflict driving states, and have therefore needed to incorporate mechanisms causing transitions to the more critical states: Either visual distraction behavior (see the section on visual distraction, as well as e.g. Xin, Hourdos, Michalopoulos, & Davis, 2008), or explicit error-generating mechanisms (see the section on simulation platforms, as well as H. Yang & Peng, 2010). In relation to the qualitative models of accident causation presented in the background, it may be noted that the error-centric approach bears clear marks of the information processing paradigm (Wickens & Hollands, 2000), whereas the visual distraction approach may be more closely tied to qualitative models such as that of Engström et al. (in press).

However, some models seem especially recommendable for use in future work: (a) The delayed constant deceleration models are, despite (or thanks to) their simplicity, noteworthy for having proved useful in a wide range of applications. The inherent limitations with respect to less critical collision avoidance need to be taken into account, however. (b) If an application requires a braking model that can also exhibit non-critical, satisficing deceleration responses, the possible signs of convergence with empirical data seen in Figure 3 suggest that the models of Wada, Imai, et al. (2007); Wada, Doi, et al. (2007); Wada et al. (2009) or Gipps (1981) can provide good starting points. (c) The Xin, Hourdos, Michalopoulos, and Davis (2008) model, which builds on the Gipps model, is unique in that it is the only model in this review to have been fitted to time series data from actual crashes. (Davis & Swenson, 2006 used the same data set, but placed less emphasis on driver modeling.) (d) Among the steering models, those that do not require explicit definition of a desired collision avoidance path seem preferable to us, assuming that they can be further validated on real crash-avoidance data (Gordon & Best, 2006; Gordon & Magnuski, 2006; Gao & Jiang, 2009). (e) If a steering model using a desired path is preferred, the approach of Plöchl and Lugner (2000) to activate a specific mechanism in cases where path deviations become large is noteworthy, since a large instantaneous shift of the desired path is one possible conceptualization of what occurs in a collision emergency. (f) Given the current lack of validation of steering models on real accident situations, it cannot be excluded that simple open-loop responses, such as those proposed by Sugimoto and Sauer (2005) or Araszewski et al. (2002), are good enough for many applications. (g) The ACT-R models of Salvucci (2006) and colleagues illustrate the potential benefits of adopting an existing cognitive architecture that has been subjected to much previous validation and tuning.

Suggestions for future model development

Comparing the reviewed models with the statements made in the background section of this paper, some suggestions can be made regarding possible areas for future model development work.

First of all, it may be noted that among the reviewed models, the models which address braking only are generally much simpler in their formulations than the models involving steering. For example, the braking models typically operate directly on vehicle acceleration or speed, rather than on the vehicle's pedals. For some applications, *more detailed models of collision-avoidance braking control* could therefore prove useful.

Another observation that can be made is that although some authors have modeled reactions to collision warnings in various ways (e.g. Fitch et al., 2008; J. D. Lee et al., 2002; Steigerwald, 2002), none of the reviewed models have addressed the phenomena of *acceptance, reliance, and behavioral adaptation to long-term system exposure*. This is not a trivial endeavor, but will be required if driver models are to be used for generating more than theoretical upper limits for predicted potential benefits of safety systems. Assuming a continued increase in proliferation of collision avoidance technology, these aspects of driver behavior are certainly worthy of modeling efforts.

Additionally, current technological trends point to an increased presence of support systems providing autonomous braking or steering interventions. *Driver avoidance behavior in interaction with control interventions from the vehicle* may take on qualitatively different forms than non-assisted avoidance, but this aspect has not been addressed in any of the reviewed papers (A possible exception is the paper by Kuge et al., 2006). Addressing this gap is desirable especially since intervening systems will require the type of rigorous testing for which simulation can be an important tool.

Furthermore, some of the reviewed models have been capable of behaviors such as visual distraction, and others have accounted for between-driver variability in collision avoidance control, but the issue of *when and why drivers adopt risky behaviors*, such as for example looking away from the road ahead, has not been addressed. In the terms used by Engström et al. (in press, presented in the background of this paper), this can be expressed as simulation models having focused mostly on the reactive barrier. In general, there is ample room for further research regarding *simulations with driver models in the study of accident causation*. Among the reviewed papers, only Davis and Swenson (2006) explicitly addressed such a goal, studying how rear-end crash responsibility may be attributable to more than one driver in a line of traffic. One possibility here could be to carry out simulations with driver models derived from competing qualitative models of accident causation, as a means of clarifying which qualitative models work best. Furthermore, several factors known to be involved in accident causation have received limited or no attention in the reviewed papers. For example, quantitative models of the *effects of alcohol and fatigue on collision avoidance* are absent altogether.

Another notable feature of many of the models, is the use of *engineering practices not in line with current knowledge of human psychology*. For example, rather than operating on the type of visual cues that human drivers seem to use (see e.g. Fajen, 2005; Wann & Wilkie, 2004), most reviewed models use high resolution data regarding, for example, longitudinal and lateral positions of vehicles. (Exceptions include the model by Wada, Doi, et al., 2007, and to some extent also those by H. Yang & Peng, 2010, Xin, Hourdos, Michalopoulos, & Davis, 2008, and Reński, 2001.) Furthermore, several driver models include features such as (a) preview, despite arguments that in urgent situations, control may shift to more short-sighted modes of operation (Hollnagel & Woods, 2005), and (b) advanced internal vehicle models, despite observations that human drivers may not have a correct grasp of the dynamics of their vehicles (Cloete & Wallis, 2009). In our opinion, psychology-oriented modelers could benefit from acknowledging that these types of practices can be powerful in the construction of phenomenological models, aimed at reproducing observed behavior data without necessarily making claims on underlying psychological (or neurobiological) mechanisms. It may however also be rightfully suggested to engineering-oriented modelers that models based on an understanding of such mechanisms could generalize better to wider scopes of application. In addition, it is our opinion that there may be logical pitfalls to avoid when using engineering methods, such as taking for granted that an inexperienced driver behaves as if having an internal vehicle model that is *mathematically* simple.

It may also be noted that the types of collision scenarios for which driver models have been developed remain limited in number, with a heavy focus on rear-end scenarios. In order to achieve full credibility of simulation as a safety research approach, models will at some point need to address *more diverse and complex pre-crash scenarios*. Similarly, it would seem relevant to widen the modeling scope to also include collision-avoidance with *other vehicles than passenger cars*. (Among the reviewed papers, X. Yang et al., 2001 provided the only exception.) It could also be relevant to study to what extent models developed for one type of scenario or vehicle may be useful for other types.

Related to this issue, the mechanisms governing *selection of maneuver type, as a function of the traffic situation*, have not been given more than marginal attention among the reviewed models. The probabilities for braking versus steering in the model of Sugimoto and Sauer (2005) were not situation-dependent, and Jurecki and Stańczyk (2009) appear not to have put their statistical observations into simulation-ready model practice. Furthermore, although some of the reviewed models could theoretically reproduce the *no-maneuver response* so often seen in real collision accidents (Wiacek & Najm, 1999), this aspect has not been studied by any of the authors.

Thus, there may be a need for considering *separate modes of collision avoidance control* (Hollnagel & Woods, 2005). Some of the reviewed models do include specific provisions for urgent situations (Plöchl & Lugner, 2000; Yuhara & Tajima, 2006; and possibly Akita et al., 2007), but an analysis of whether or not this is preferable is lacking. Currently it seems unclear whether critical avoidance is best modeled with (a) the same models as for normal avoidance, giving different response to the critical situation, (b) different parameterizations of the normal avoidance models, or (c) different models altogether.

In general, we would argue that none of the reviewed models have fully adopted the view of *critical collision-avoidance maneuvering as a highly unexpected and unusual task*. As suggested in the background above, behavior may become erratic or random in accident situations. Furthermore, if drivers do attempt more controlled maneuvers, their perceptual attunement to the critical situation may be limited, resulting in misinterpretations or maladjusted control actions. These aspects remain largely unexplored in current simulation models of driver behavior.

Model validation and comparison

Many of the reviewed models are capable of making highly detailed predictions on drivers' use of pedals and steering wheel during collision avoidance, as well as the effects on this control of various driver-related factors. However, validation of the models on relevant human data has rarely been achieved to the same level of detail. One important reason for this is probably that it is far from trivial to collect data on collision avoidance behavior, especially if the data are to be representative of behavior in unexpected collision situations in real traffic. Hopefully, recent and ongoing naturalistic driving studies (see e.g. Dingus et al., 2006) can provide researchers with better possibilities to achieve good model validation.

It is also clear, however, that even with good data, it is not evident how to carry out validation. In many papers, validation seems to have been limited to visual estimation of the match between time-series data on human and parameter-fitted driver model behavior. Although far beyond the scope of this discussion, *more ambitious and rigorous methodologies for quantitative validation of driver models* definitely seem to be needed. When the aim of a model is to test hypotheses on underlying psychological mechanisms, it needs to be shown that successful fits of observed data are not simply due to a highly flexible model (Roberts & Pashler, 2000). In applied contexts, model flexibility may be less of a problem, but it still needs to be shown (e.g. by means of cross-validation or holdout validation techniques; see Hastie, Tibshirani, & Friedman, 2009, p. 222) that a proposed parameter set is not the result of over-fitting to the human behavior data used. Another possible perspective is that, due to the stochastic nature of crashes, validation of models addressing near-collision control behavior may need to operate rather on *distributions* of trajectories or of other measures of behavior. For models covering also normal driving, the approach of comparing simulated crash frequency to accident statistics (see e.g. H. Yang & Peng, 2010), may be one important part of a validation methodology.

Regardless of how the agreement between model and data is quantified, an important future development would be an increase in the practice of *comparing driver models in actual simulation*. Already the very basic comparisons presented in this review suggest dissimilarities and similarities which may not have been evident from the mathematical formulations of the compared models. The left panel of Figure 2 illustrates the fundamental difference between satisficing and non-satisficing models of braking. Figure 3 indicates a possible convergence, in terms of non-critical brake initiation timing, between the models of Gipps (1981) and Wada et al. (2009) on the one hand, and the data set of Kiefer et al. (2005) on the other. For researchers who are mainly interested in whether or not a given simulated scenario results in a collision or not, Figure 4 can be taken to suggest that it may be enough to adopt a rather simple model of avoidance by steering: For example, all models would have avoided a stationary obstacle at a longitudinal position of 40 m.

In our opinion, comparison of models ought to be much more frequent in this research field than it currently is. As is clear from the present review, for a given traffic scenario or behavioral phenomenon, there are often several competing driver models, but it is rarely known how these models differ in terms of their behavior, or in terms of how well they are able to reproduce the corresponding behavior of human drivers. In order for novel near-collision behavior models to be of value, either from a scientific or an applied point of view, their development should be complemented with comparative investigations. Some model developers who have set good examples in this respect are K. Lee and

Peng (2004), Ungoren and Peng (2005), and MacAdam (2003).

Concluding remarks

We have provided a review of recent simulation-ready models of driver behavior in accident situations involving on-road collisions. The results show a somewhat fragmented research field, in which many different models have been proposed for a wide variety of applications. However, based on the results obtained from simulations of existing models, we suggest that, in some cases, there may be more similarity between the models than what is immediately apparent from the corresponding equations.

Some models have been identified that may deserve attention in future work. However, it has also been emphasized that, due to the complexity of the processes being modeled, it seems likely that for the foreseeable future, the scope of requirements to set for a driver model will need to be strictly limited to fit the intended context of application.

Specific suggestions for future work on model development have been made, but it has also been argued that a major remaining challenge is an improved paradigm for validation and comparison of already existing models.

Key points

- Computer simulation of accident situations holds promise as a valuable tool for traffic safety research.
- This paper is a review of near-collision driver behavior models that are suitable for use in computer simulation.
- A wide variety of models has been proposed, but validation on collision-relevant human behavior data has so far often been limited.
- Simulation-based comparison suggests some non-trivial similarities between existing models, and further comparison of this kind is recommended.

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Appendix A
Literature database searches

Databases searched: ARL, IEEE Xplore, ISI Web of Science, Inspec, PubMed, SAE, Scopus, TRIS.

Search queries varied depending on search syntax and the features of the individual databases. Example for Scopus: `TITLE-ABS-KEY((collision* or accident* or incident* or safety or "driv* support" or "driv* assistance") AND (simulat* or quantitative or mathematic* or model*) AND (driver W/6 model*)) AND PUBYEAR AFT 1999`

Appendix B
Vehicle model parameters

Table B1
: Vehicle model parameters (Thommyppillai et al., 2009, p. 1538), used when simulating driver steering models (see Figure 4).

Parameter	Symbol	Value	Unit
Mass	M	1400	kg
Yaw inertia	I_z	2500	kg m^2
Front axle distance	a	1.16	m
Rear axle distance	b	1.54	m
Steering gear ratio	G	17	-
Stiffness factor	B_m	11.5	-
Shape factor	C_m	1.3	-
Peak factor	D_m	2500	N
Curvature factor	E_m	0.3	-

Paper V

Comparing and validating models of driver steering behaviour in collision avoidance and vehicle stabilization

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RESEARCH ARTICLE

Comparing and validating models of driver steering behaviour in collision avoidance and vehicle stabilization

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A number of driver models were fitted to a large data set of human truck driving, from a simulated near-crash, low-friction scenario, yielding two main insights: Steering to avoid a collision was best described as an open-loop manoeuvre of predetermined duration, but with situation-adapted amplitude, and subsequent vehicle stabilization could to a large extent be accounted for by a simple yaw rate nulling control law. These two phenomena, which could be hypothesized to generalize to passenger car driving, were found to determine the ability of four driver models adopted from literature to fit the human data. Based on the obtained results, it is argued that the concept of internal vehicle models may be less valuable when modelling driver behaviour in non-routine situations such as near-crashes, where behaviour may be better described as direct responses to salient perceptual cues. Some methodological issues in comparing and validating driver models are also discussed.

Keywords: Driver models, steering, collision avoidance, low friction, driving experience, electronic stability control

Manuscript word count: 7501 words including appendix

1. Introduction

It is well established that driver behaviour plays a prominent role in the causation of traffic accidents [1, 2], and considerable research effort has been spent on understanding and describing driver behaviour in near-crash situations. This is not an easy object of study, but as a result of accident reconstructions, large-scale naturalistic data collection projects, and experiments on test tracks and in driving simulators, there is a growing body of knowledge on the various reasons why drivers end up in critical situations, such as inattention [3] or incorrect expectations [4, 5], and on how drivers typically control the vehicle if and when they try to avoid an imminent crash [6–9].

An important application of such knowledge is the construction of quantitative models of driver control behaviour in near-crash situations. When put to use in computer simulations, such models permit cost-efficient safety performance optimization of, for example, infrastructure designs [10], vehicle designs [11], or active support systems that provide warnings or control interventions [12–14].

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There is a wealth of existing driver behaviour models that could be useful in such simulation-based research efforts, reviewed in [15–19]. However, a recent review, focusing specifically on models that have been applied in simulation of near-collision situations [20], noted two clear limitations in the literature: (a) With just a few exceptions [21–23], new models have been proposed without comparing their behaviour to that of existing, alternative models, making it difficult to know which models to prefer for a given application. (b) Validation of model behaviour against human behaviour data from real or reasonably realistic near-crash situations has been virtually non-existent. Many models of steering control were found to have been validated against human behaviour in predefined test-track manoeuvres, for example a double lane change [24]. However, such tests seem rather unlike real-life, unexpected near-crash situations, and could potentially elicit qualitatively different behaviours from drivers [25–27].

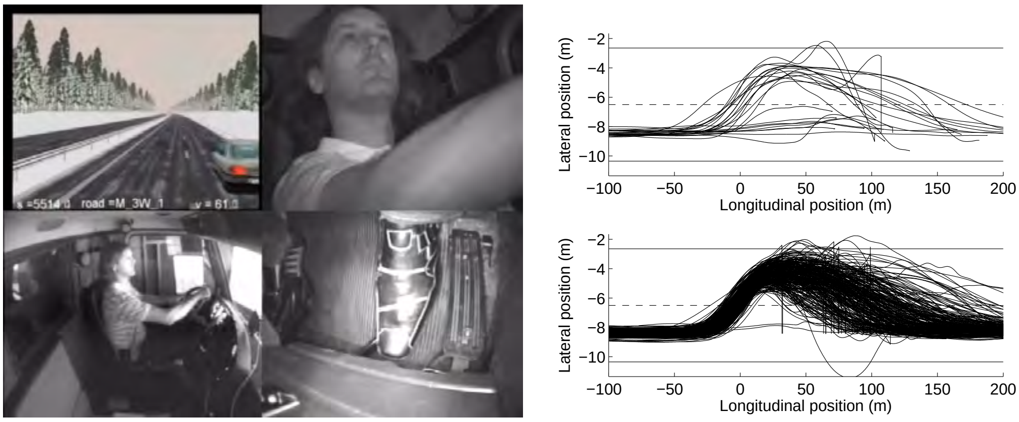
This paper addresses both of the two above-mentioned limitations, in the specific context of collision avoidance and subsequent vehicle stabilization, on a low friction road surface. One use for models validated in this type of context is simulation-based evaluation of vehicle stability support systems such as *electronic stability control* (ESC) [28–31]. In [32], it was shown that one existing driver model could reproduce the stabilization steering behaviour observed after unexpected and expected near-collisions in a driving simulator study, previously described in [33]. Here, the analysis of this dataset, fitting models separately to each human driver, will be extended to include also the collision avoidance phase of the studied scenario, and to include a comparison of a number of existing and novel models of steering.

The next section will describe the data collection simulator study and the driver models, as well as the method for fitting the models to the human steering data. Then, model-fitting results will be provided, including some analysis of the obtained model parameters. The subsequent discussion will highlight differences between the models and their respective strengths and weaknesses in the studied scenario, as well as some challenges involved in model comparison and validation.

2. Method

2.1. *Data collection*

The human driving data used here were collected in the moving-base driving simulator *VTI Simulator II* in Linköping, Sweden. Full details on the simulator and the experimental procedures adopted in this study can be found in [33]. In summary, 48 drivers, driving a three-axle rigid simulated truck (6.2 m from first to last axle) at 80 km/h, experienced an unexpected lead vehicle deceleration scenario on a low-friction ($\mu = 0.25$) road surface. Half of the subject drivers subsequently also experienced the same scenario an additional twelve times each, in a novel paradigm for repeated collision avoidance, and it is this 24-driver repeated-scenario data set which is used here. Half of the 24 drivers were novices, who had just obtained, or were just about to obtain, their heavy truck driving license, and half were experienced drivers, with at least six years of professional experience in commercial operations. In half of all measurements, the simulated truck had an active ESC system, a software-in-the-loop implementation of the actual Volvo Trucks on-market ESC, and in the other half of measurements drivers were aided only by the anti-lock braking system (ABS). The critical scenario, requiring a steering manoeuvre for successful collision avoidance, is illustrated in Fig. 1, together with an overview of the observed vehicle trajectories.



(a) (b)

Figure 1. The studied critical scenario. (a) A screenshot from the experiment video log, showing the two-lane winter road on which the maneuvering took place, the braking lead vehicle, and a subject engaged in steering collision avoidance. (b) The totality of observed vehicle trajectories, in the unexpected (top panel) and repeated (bottom panel) scenarios. Horizontal gray lines show lane boundaries, and each black line shows the movement of the front center of the truck in one recorded event. Longitudinal position zero corresponds to the point where the front of the truck reached the rear of the lead vehicle. The unexpected scenario data are not used in the model-fitting analyses presented in this paper, but are shown here to illustrate that the two scenarios generated roughly similar human behaviour; see further [32] and [34].

It has been demonstrated elsewhere that the unexpected and repeated scenarios generated similar initial steering avoidance situations [33, 34], and elicited similar driving steering behaviour, both during collision avoidance [34] and stabilization [32].

2.2. *Tested models*

The set of driver models to test was defined so as to include both some well-known path-following models of steering, often available in off-the-shelf software for e.g. simulating predefined manoeuvres (the MacAdam and Sharp *et al.* models), as well as models of routine lane-keeping which may be less familiar but which take different, and in our view promising, modelling approaches (the Salvucci & Gray and Gordon & Magnuski models). Furthermore, based on the results from parameter-fitting these existing models to the behaviour of the human drivers, two very simple additional models of steering were developed, one targeting collision avoidance only, and the other targeting only vehicle stabilization. Below, all tested models will be briefly described, along with specific implementation details when needed. For ease of reading, consistent notation is used for quantities that are shared across models, in some cases departing from the symbols used by the original authors.

2.2.1. The MacAdam model

At a given time t, the model proposed by MacAdam [35], illustrated in Fig. 3(a), applies the steering wheel angle $\delta(t)$ that minimizes the predicted lateral deviation from a *desired path*, by minimizing the following functional:

$$J(t) = \int_{t-T_{\mathrm{R}}}^{t-T_{\mathrm{R}}+T_{\mathrm{P}}} \left(f(\eta) - y(\eta)\right)^2 d\eta \qquad (1)$$

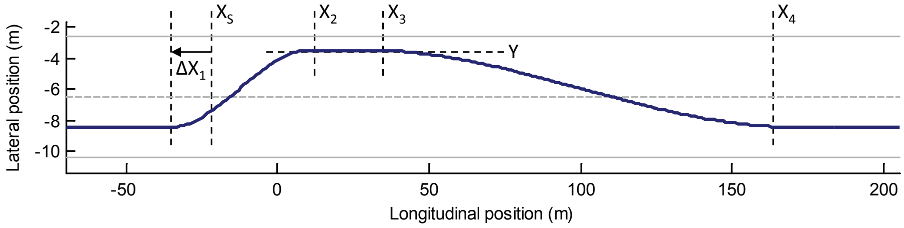


Figure 2. The desired path used for the MacAdam [35] and Sharp *et al.* [36] models, with ΔX_1, X_2, X_3, X_4, and Y as driver-specific model parameters. The two lane changes are cubic splines with lateral speed zero at beginning and end. Before and after the manoeuvre, desired lateral position is set to the middle of the right driving lane. Longitudinal position zero corresponds to the point where the front of the truck reached the rear of the lead vehicle, and X_S is the longitudinal position at which the human driver's collision avoidance steering reached half of its maximum value, in a specific recorded instance of the critical scenario.

In Eq. (1), $y(t)$ and $f(t)$ are the predicted and desired lateral positions, and T_R and T_P are model parameters corresponding to a *reaction time* and a *preview time*, respectively. Here, the desired path $f(t)$ of the vehicle was defined as shown in Fig. 2, using model parameters ΔX_1, X_2, X_3, X_4, and Y. In order to allow for intra-driver variability in the exact point of collision avoidance initiation, the lane change to the left was set to start at a longitudinal position $X_\mathrm{S} - \Delta X_1$, where X_S was the longitudinal position at which the steering wheel reached half of its maximum leftward deflection (i.e. X_S had a unique value for every recorded instance of the critical scenario).

The MacAdam model's prediction $y(t)$ of lateral position relies on a linear *internal vehicle model*. Here, the same classical type of one-track model as used by MacAdam [35] was adopted, but with three axles instead of two:

$$\dot{\mathbf{x}} = \mathbf{F}\mathbf{x} + \mathbf{g}\delta = \begin{bmatrix} -\frac{C_{\alpha f}+C_{\alpha m}+C_{\alpha r}}{m v_x} & \frac{-aC_{\alpha f}+bC_{\alpha m}+cC_{\alpha r}}{m v_x} - v_x \\ \frac{-aC_{\alpha f}+bC_{\alpha m}+cC_{\alpha r}}{I_z v_x} & -\frac{a^2C_{\alpha f}+b^2C_{\alpha m}+c^2C_{\alpha r}}{I_z v_x} \end{bmatrix} \mathbf{x} + \begin{bmatrix} \frac{GC_{\alpha f}}{m} \\ \frac{GaC_{\alpha f}}{I_z} \end{bmatrix} \delta \quad (2)$$

where $\mathbf{x} = [v_y\ \dot{\psi}]^T$, v_x and v_y are longitudinal and lateral speeds in the vehicle's reference frame, and ψ is the yaw angle of the vehicle. The three $C_{\alpha\cdot}$ parameters and a, b, c are tire cornering stiffnesses and longitudinal distances to the vehicle's mass centre, for the front, middle, and rear axles, respectively. The parameters m and I_z are vehicle mass and moment of inertia, and G is the steering gear ratio.

Since the linear vehicle model cannot account well for skidding, it was parameter-fitted only to recordings with maximum body slip angle $\beta < 1°$ (3 % of the total data set). This can be understood as assuming that drivers had acquired an understanding of vehicle dynamics from normal, high-friction driving, and applied this understanding also during yaw instability[1]. Only the three cornering stiffnesses were fitted to the data; the other parameters were taken from the non-linear model used in the simulator study. Fig. 4 illustrates the resulting model performance at various magnitudes of yaw instability.

2.2.2. The Sharp et al. model

The model proposed by Sharp *et al.* [36] also makes use of the desired path construct, but, as illustrated schematically in Fig. 3(b), instead calculates its steering wheel input as a weighted sum of current and previewed path deviations e_i along a forward *optical lever*, extending a preview time T_P ahead, and the current deviation

[1]Various approaches were explored for fitting the linear model also to recordings with more severe yaw instability, but were not found to improve the fit of the resulting driver model.

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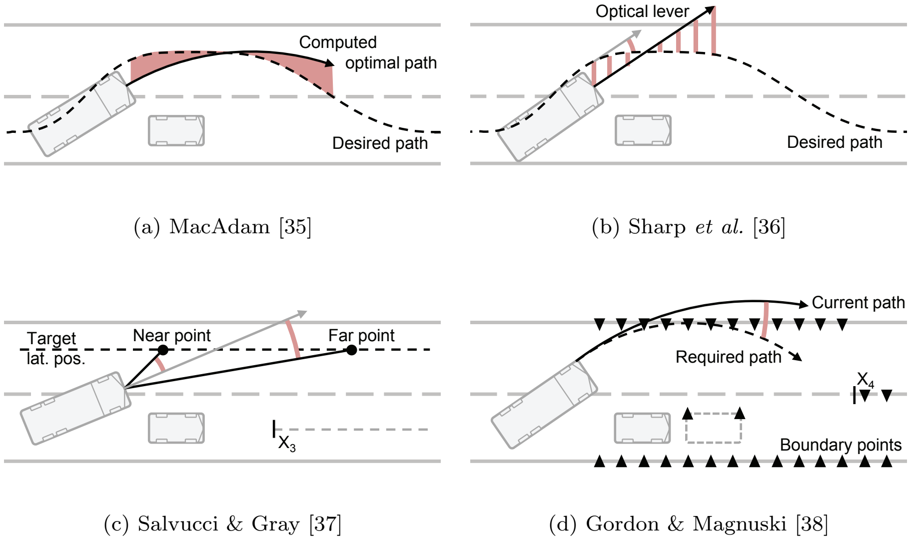


Figure 3. Schematic illustrations of the models adopted from literature.

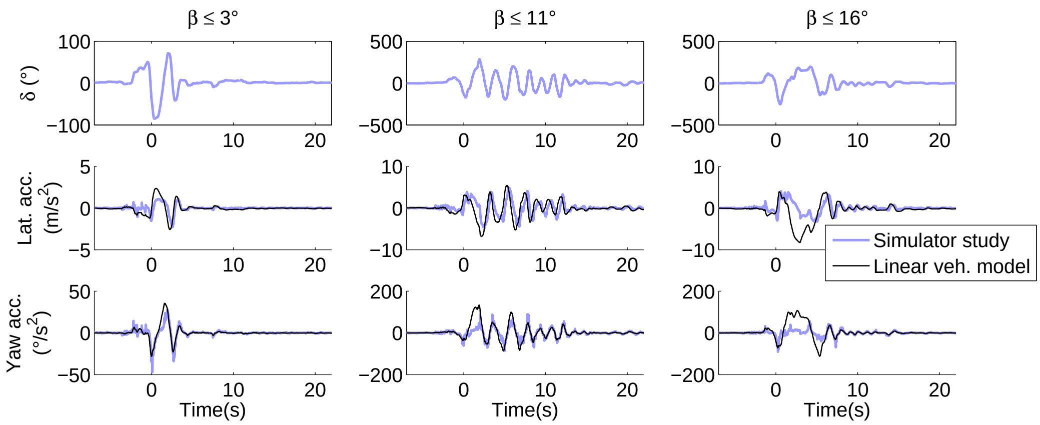


Figure 4. The top row of panels show observed steering wheel movements in three recordings of the repeated scenario, with maximum attained body slip angles β increasing from left to right. The bottom two rows of panels show, for the same recordings, the observed vehicle dynamics from the full non-linear vehicle dynamics model used in the data collection experiment, compared with the vehicle dynamics predicted by the linear model used with the MacAdam driver model in this paper.

e_ψ between vehicle and path heading:

$$\delta = K_\psi e_\psi + K_1 e_1 + K_\mathrm{p} \sum_{i=2}^{n} K_i e_i \tag{3}$$

Here, K_ψ, K_1, and K_p were treated as free model parameters, whereas the number n of preview points, their spacing along the optical lever, and the exponentially decreasing profile for the preview gains K_i (with $2 \leq i \leq n$) were adopted from [36]. Additionally, to allow for a fair comparison with the other models, a reaction time delay parameter T_R was added to Eq. (3). The saturation functions included by Sharp *et al.* with the purpose of "preventing the steer angle from exceeding a reasonable range"[36, p. 312], were not included.

2.2.3. The Salvucci and Gray model

The model by Salvucci & Gray [37] is mathematically rather similar to the Sharp *et al.* model. However, instead of being derived from linear optimal control theory, it builds on experiments and modelling in psychology, motivating: (a) the use of the rate of change $\dot{\delta}$ of steering as an input variable rather than δ [39], and (b) the separation of controlled quantities (the input to the driver) into one *near point* and one *far point* [40] on a target lateral position, as illustrated in Fig. 3(c). It is assumed that the driver aims to keep the the sight angles θ_n and θ_f to these points stationary, while at the same time attempting to reduce the near point angle to zero:

$$\dot{\delta} = k_\mathrm{nP}\dot{\theta}_\mathrm{n} + k_\mathrm{f}\dot{\theta}_\mathrm{f} + k_\mathrm{nI}\theta_\mathrm{n} \tag{4}$$

In addition to the gain parameters in Eq. (4), free parameters were also included for the longitudinal distances D_n and D_f to the near and far points, respectively[1], as well as a reaction time T_R. Analogously to the desired path of the models described above, the target lateral position was initially set to the middle of the right lane, then set to a position Y when the truck reached longitudinal position $X_\mathrm{S} + \Delta X_\mathrm{I}$, and then back to the middle of the right lane at longitudinal position X_3. To test the sensitivity of the model to the preview distance parameters, an additional version of the model was tested, where these parameters were fixed, for all drivers, at the median values $D_\mathrm{n} = 16$ m and $D_\mathrm{f} = 123$ m, observed in the optimizations where these parameters were left free.

2.2.4. The Gordon and Magnuski model

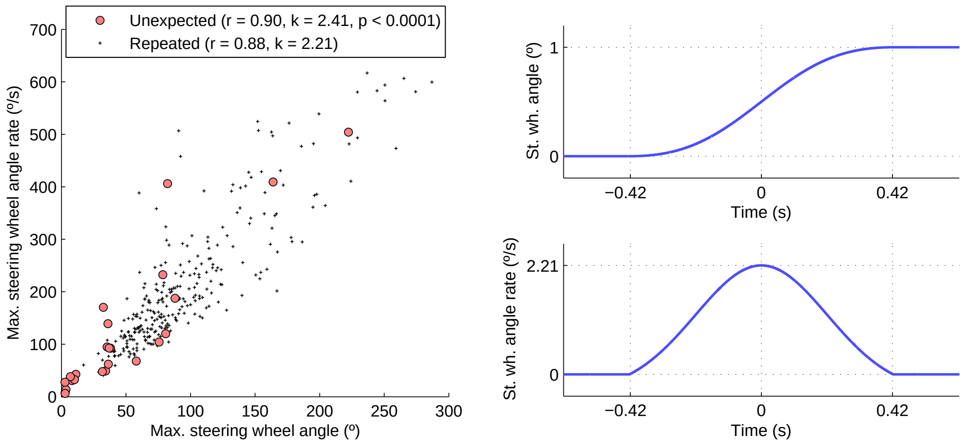
Since the models described above all aim at reducing the deviation from a desired path or lateral position to zero, they could be referred to as *optimizing* models. In contrast, the model by Gordon & Magnuski [38], illustrated in Fig. 3(d), operates in what can be called a *satisficing* [41] manner: It assumes that the driver is content with staying inside a delimited region, modelled using *boundary points*. Specifically, the model compares the current yaw rate to the yaw rates needed to steer clear of each boundary point, identifies the point with the greatest mismatch, and applies a rate of steering aimed at reaching, within a time τ_s, the required yaw rate $\dot{\psi}_\mathrm{req}$ for this point, assuming a simple vehicle model with wheel base L:

$$\dot{\delta} = -\frac{L}{G\tau_\mathrm{s}v_x}(\dot{\psi} - \dot{\psi}_\mathrm{req}) \tag{5}$$

Before computing $\dot{\psi}_\mathrm{req}$, the model also applies a vehicle state prediction to counteract its own reaction time delay T_R.

The original publication [38] considered only lane keeping, but Chang [42] applied the same model to avoidance of static obstacles, with a safety margin ρ_C. In the present work, seemingly the first time the model is applied to obstacles and lane boundaries simultaneously, conflicts with lead vehicle boundary points were given priority over lane boundary conflicts, and a separate safety margin ρ_L for lane boundaries was added, with allowed negative values in the optimization, to account for the apparent acceptance of moderate lane excursions in some of the

[1]Following [40], Salvucci & Gray [37] specified preview in terms of angles down from the horizon, which in practice amounts to the same as using a preview distance. Here, it was also attempted to make the preview speed-dependent, as in the MacAdam and Sharp *et al.* models, e.g. $D_\mathrm{n} = T_\mathrm{n}v_x$, but if anything this reduced the model's ability of fitting the human data.



(a) (b)

Figure 5. Open loop avoidance steering. (a) The observed correlation between maximum leftward steering wheel angle before reaching the lead vehicle, and maximum leftward steering wheel angle rate during the same period. The Pearson correlation coefficients r are provided, as well as the slope k of least-squares fit lines with zero intercept. The unexpected scenario data are not used in the model-fitting analyses presented in this paper, but are shown here to illustrate that the two scenarios generated roughly similar human behaviour; see further [32] and [34]. (b) The steering wheel input generated by the open loop avoidance model in this paper, here parameterized to illustrate the width of such a steering wheel pulse (0.84 s) that would yield the k observed for the repeated scenario in panel (a).

human drivers. Furthermore, extending the model to handle the non-static lead vehicle, lead vehicle state prediction was included, as also illustrated schematically in Fig. 3(d). In three different versions of the model, this prediction was done assuming a constant lead vehicle acceleration (2$^{\text{nd}}$ order), speed (1$^{\text{st}}$ order), and position (0$^{\text{th}}$ order), respectively. To implement the scenario studied here, the lead vehicle boundary points were included only from longitudinal position $X_{\text{S}} + \Delta X_{\text{I}}$, and the lane change back to the right lane was achieved by placing the left-side boundary points beyond longitudinal position X_4 to between the two driving lanes; again, see Fig. 3(d).

2.2.5. Open loop avoidance models

An additional model of collision avoidance steering was tested, motivated by a linear correlation previously reported by Breuer [25], and replicated here: As shown in Fig. 5(a), higher-amplitude avoidance manoeuvres were carried out with faster steering movements. This finding suggests (a) that avoidance manoeuvre duration was roughly constant between scenario recordings, and (b) that each manoeuvre's amplitude was determined *before* its initiation.

Therefore, in contrast to the *closed-loop* models described above, which calculate a new control input at each time step in a simulation, an *open-loop* model was posited, applying a pulse of steering wheel rotation represented as a Gaussian cut off at ± 2 standard deviations; see Fig. 5(b). The pulse duration $T_{\text{D}} = 2T_{\text{H}}$ was included as a free parameter, and pulse amplitude was determined as a function of the collision situation a reaction time T_{R} before manoeuvre initiation. To allow for the above-mentioned intra-driver variation in collision avoidance timing, the peak of the pulse was placed at time $T_{\text{S}} + T_{\text{A}}$, where T_{S} was the time at which the truck's longitudinal position was X_{S} (see above), and T_{A} was another free model parameter.

Five different versions of the model were tested, all using a model parameter K to determine the steering pulse amplitude as (a) a constant, situation-independent amplitude K, (b) K times the *optical expansion*, or *looming*, of the lead vehicle on the driver's retina [43], or (c-e) K times the steering required to avoid the lead vehicle with a safety margin ρ_C, given the steady state yaw rate response of the linear vehicle model described in 2.2.1, and a lead vehicle state prediction of orders zero through two (cf. Sec. 2.2.4).

While this model is neutral on whether the driver is controlling steering wheel angle δ or its rate of change $\dot{\delta}$, the choice of target signal has an impact on model parameter-fitting (further discussed in Sect. 4.3). Therefore, this model was fitted separately both as controlling δ and $\dot{\delta}$.

The model's sensitivity to the T_R parameter was also tested, by parameter-fitting an additional version of the δ-controlling, 2$^{\mathrm{nd}}$ order yaw rate requirement model, with T_R fixed at 0.2 s for all drivers.

2.2.6. Yaw angle/rate nulling stabilization models

As has been reported elsewhere [32], the Salvucci & Gray model is reasonably successful at fitting the stabilization steering data studied here. Additional exploration indicated that much of the variance explained by the model was accounted for by its far point control (the second term in Eq. 4), shown in [32] to approximate a *yaw rate nulling* steering behaviour: $\dot{\delta} = -K\dot{\psi}$, where K is a model parameter. Here, such a model was tested directly, as well as a time-integrated *yaw angle nulling* version $\delta = -K\psi$, both with a reaction time delay T_R.

2.3. *Division into avoidance and stabilization steering phases*

Preliminary experimentation indicated that the steering models were differentially successful at fitting steering during collision avoidance and vehicle stabilization. Therefore, the data set was split accordingly, and model parameter-fitting was carried out separately on the two sets.

The *collision avoidance phase* of a recorded scenario was defined to begin when the lead vehicle started decelerating, and to end when the driver began applying considerable rightward steering wheel rotation, interpretable as a transition from leftward collision avoidance, to lane alignment and vehicle stabilization. This onset of rightward steering wheel rotation was generally clearly visible in the data, and was found to be suitably defined as the last point of leftward steering ($\delta > 0$) where $\dot{\delta} > -50°$/s. The example recordings in Fig. 6 (further explained in Sect. 3) illustrate where this transition typically occurred.

The *stabilization phase* was defined to begin at the same transition point, and to end at whichever occurred first of (a) the truck having travelled 250 m after passing the lead vehicle, (b) the truck's longitudinal speed falling below 10 km/h, or (c) the driving simulator's safety shutdown system having aborted the scenario due to road departure, or a deviation of truck heading from the road's forward direction of 90° or more.

2.4. *Model parameter-fitting*

The repeated scenario generated 12 measurements for each of the 24 subject drivers except three, where, due to technical shortcomings, or subject failure to comply with experimental instructions, one or two scenario instances could not be recorded or used. Before parameter-fitting of models, all recorded signals were down-sampled to 5 Hz. The main motivation for down-sampling was the increase in optimization speed, but it could also be argued that at high sample rates, adjacent data points would anyway be highly correlated, and the input quantities to the tested models, all constrained by the dynamics of the truck on the road, would also not be expected to contain much valuable information frequencies above 5 Hz.

At each included data point i, a model undergoing parameter-fitting was fed its required input data from the appropriate recorded signals, with delays if applicable, and the goal of the parameter-fitting, implemented using a *genetic algorithm* (GA), was to achieve a model output $\hat{x}_i$ as close as possible to the observed human control x_i at the same point in time, with x_i equal to either δ_i or $\dot{\delta}_i$, depending on the model[1]. For further information on GA optimization in general, see [44], and see Appendix A for full details on the specific GA used here.

To quantify model fit, the *coefficient of determination* R^2, interpretable as the fraction of steering variance being explained by the model [45], was calculated for each scenario S as:

$$R^2 = 1 - \frac{SS_R}{SS_T} = 1 - \frac{\sum_{i \in S}(\hat{x}_i - x_i)^2}{\sum_{i \in S}(x_i - \bar{x}_S)^2} \tag{6}$$

where $\bar{x}_S$ is the average of x_i, for $i \in S$. In other words, R^2 can be negative, if a model provides a worse model fit than simply guessing that $\hat{x}_i = \bar{x}_S$ for all $i \in S$.

Holdout validation [44] was adopted: For each subject driver, the set of available recorded scenarios was divided into one *training set* and one *validation set*, of equal size[2]. The GA was set up to maximize the average of R^2 across the scenarios in the training set, but, in order to prevent *over-fitting*, the final model parameterization was selected as the parameterization with highest average R^2 across the validation set. The allocation of recorded scenarios to the two sets was designed to balance the amount of occurring vehicle instability between them: For each driver, the recorded scenarios were ordered by increasing maximum body slip angle, this ordered list was separated into pairs, and finally one randomly selected scenario in each pair was assigned to the training set, and the other to the validation set.

Thus, for each of the 24 drivers and each of the two steering phases, one optimization was carried out of each tested driver model. The total number of training and validation data points x_i used for one optimization ranged from 200 (avoidance steering for a subject with only ten recorded scenarios) to 900 (stabilization steering for a subject with twelve recorded scenarios).

3. Results

Table 1 summarizes the model-fitting results, per model and steering phase, as the average validation R^2 across the 24 drivers. Also listed are the numbers of effective free model parameters (N_{eff}), based on whether parameters were considered to have an effect on steering in the two phases; see Appendix A for full details. Note that the open loop avoidance model appears in the table both as a δ and $\dot{\delta}$ controlling model (see Sect. 2.2.5).

Figs. 6 and 7 show, in their leftmost columns, distributions of per-driver validation R^2 for some of the best-fitting model variants. It can be observed that the

[1]Alternatively, one could have rerun the studied scenario in closed-loop simulation from initial conditions, fitting parameters to achieve a match between resulting driver steering histories or vehicle trajectories. Such an approach was not adopted here, both due to it being several orders of magnitude more computation-intensive, and since the inherent instability of the low-friction scenario would presumably have rendered fitting very difficult; a small error in driver model or initial conditions can lead to large deviations in scenario outcome.

[2]Except for one single subject driver where the number of available instances was odd, for which one more instance was allocated to the training set.

Table 1. Effective number of model parameters (N_{eff}) and average goodness-of-fit (R^2) on validation data, across all drivers, for all tested models in the avoidance and stabilization steering phases. Note that some models were tested in only one of the two phases.

Target signal	Model	Variant	Avoidance N_{eff}	Avoidance Av. R^2	Stabilization N_{eff}	Stabilization Av. R^2
Steering wheel angle	MacAdam		6	0.49	5	0.50
	Sharp et al.		9	0.46	8	0.60
	Open loop avoidance	constant	3	-1.20		
		looming	4	0.71		
		0^{th} order	5	0.54		
		1^{st} order	5	0.66		
		2^{nd} order	5	0.76		
		2^{nd} order, T_{R} fixed	4	0.75		
	Yaw angle nulling				2	0.35
Steering wheel angle rate	Salvucci & Gray	preview free	8	0.20	8	0.68
		preview fixed			6	0.68
	Gordon & Magnuski	0^{th} order	5	0.25	4	0.49
		1^{st} order	5	-0.02	4	0.50
		2^{nd} order	5	0.17	4	0.50
	Open loop avoidance	constant	3	0.41		
		looming	4	0.46		
		0^{th} order	5	0.47		
		1^{st} order	5	0.40		
		2^{nd} order	5	0.47		
	Yaw rate nulling				2	0.54

spread across drivers was rather similar between models. Further divisions into subgroups based on driver experience and ESC state indicated limited or no impact of these factors on model fit; one example of such a division can be seen in Fig. 9(a). Based on these observations, the discussion in the next section will compare models mainly in terms of the average validation R^2 values in Table 1. As a complement to this perspective, and to provide a more thorough grasp of actual model behaviour, Figs. 6 and 7 also show five example scenario recordings each, along with model predictions. These examples were selected to include driving both with and without ESC for both low and high experience drivers, to illustrate some specific strengths and weaknesses of the different models, while at the same time aiming for an average R^2 across the examples close to the average validation R^2 for each model. The discussion in the next section will provide suggestions on how to interpret the various examples.

Fig. 8 shows distributions of obtained parameters for the parameter-reduced variants of the open loop avoidance and Salvucci & Gray models, as well as for the yaw rate nulling model. The correlation between the safety margin ρ_{C} and the steering gain K in panel (a) is statistically significant[1] ($r = -0.76$; $p < 0.0001$), but the difference in the steering pulse duration T_{H} between experience groups in panel (b) is not ($t(22) = 0.654$; $p = 0.51$). The correlation between the steering gains k_{f} and k_{nP} in panel (c) is statistically significant ($r = -0.71$; $p = 0.0001$), and so is the difference in reaction time T_{R} between experience groups for the Salvucci & Gray model (panel (d); $t(22) = -2.19$; $p = 0.039$); however not for the yaw rate nulling model (panel (e); mean T_{R} 0.29 s and 0.34 s for experienced and novice drivers; $t(22) = 1.82$; $p = 0.083$). The correlation between T_{R} and K in panel (e) is statistically significant ($r = -0.58$; $p = 0.003$).

[1]A $p < 0.05$ criterion for statistical significance is adopted here.

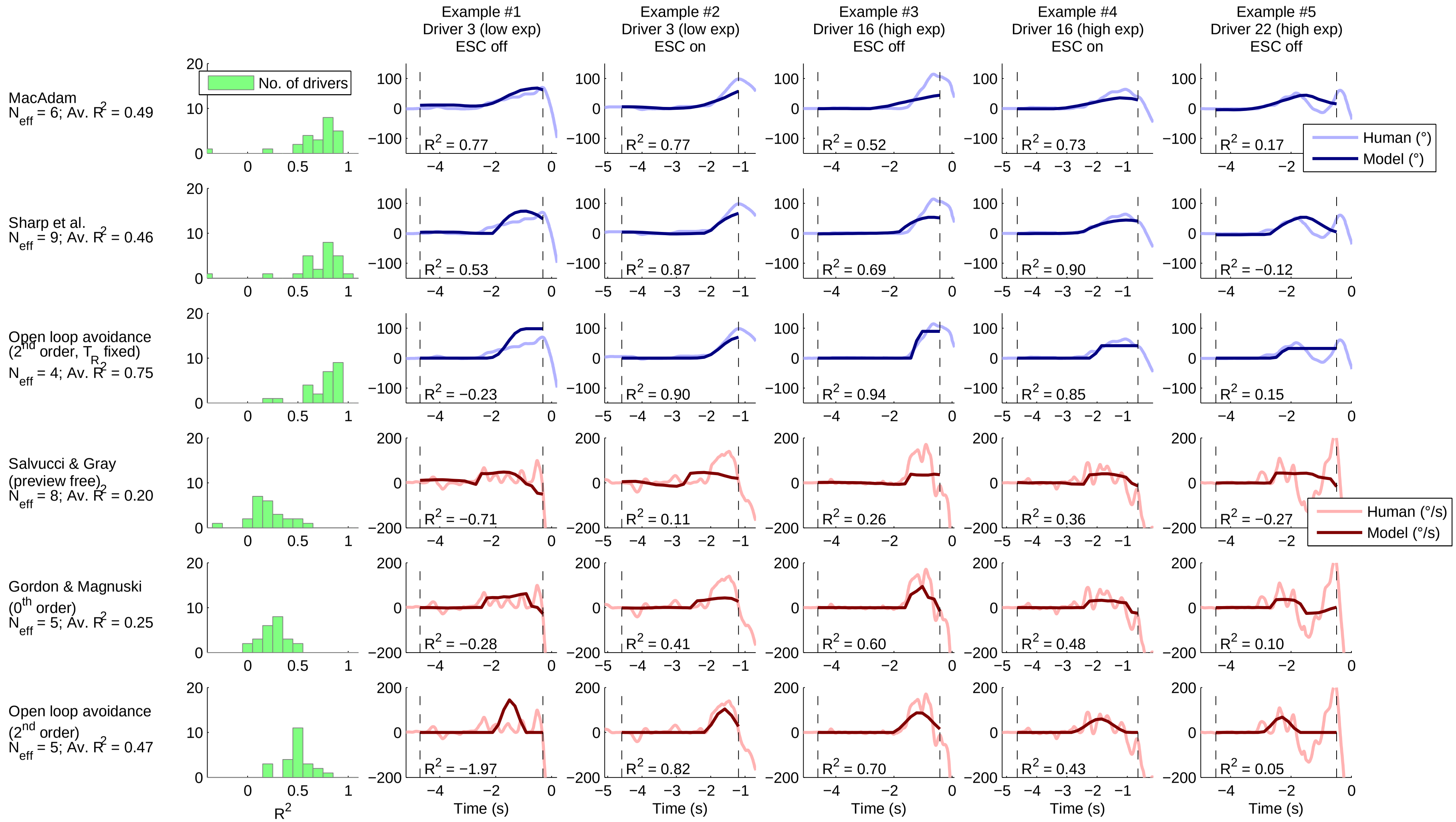


Figure 6. Collision avoidance steering. Distributions of average model performance (leftmost panels) and comparison of human and model steering in five example recorded scenarios, for six of the tested models. Besides including both novices and experienced drivers, driving with and without ESC, the example recordings have been chosen to illustrate typical model performance across various steering behaviours, and to highlight strengths and weaknesses of the different models. Note that the top three rows show models controlling steering angle (δ), whereas the bottom three show models controlling steering rate ($\dot{\delta}$), thus deviating somewhat from the order of model presentation in Sect. 2.2.

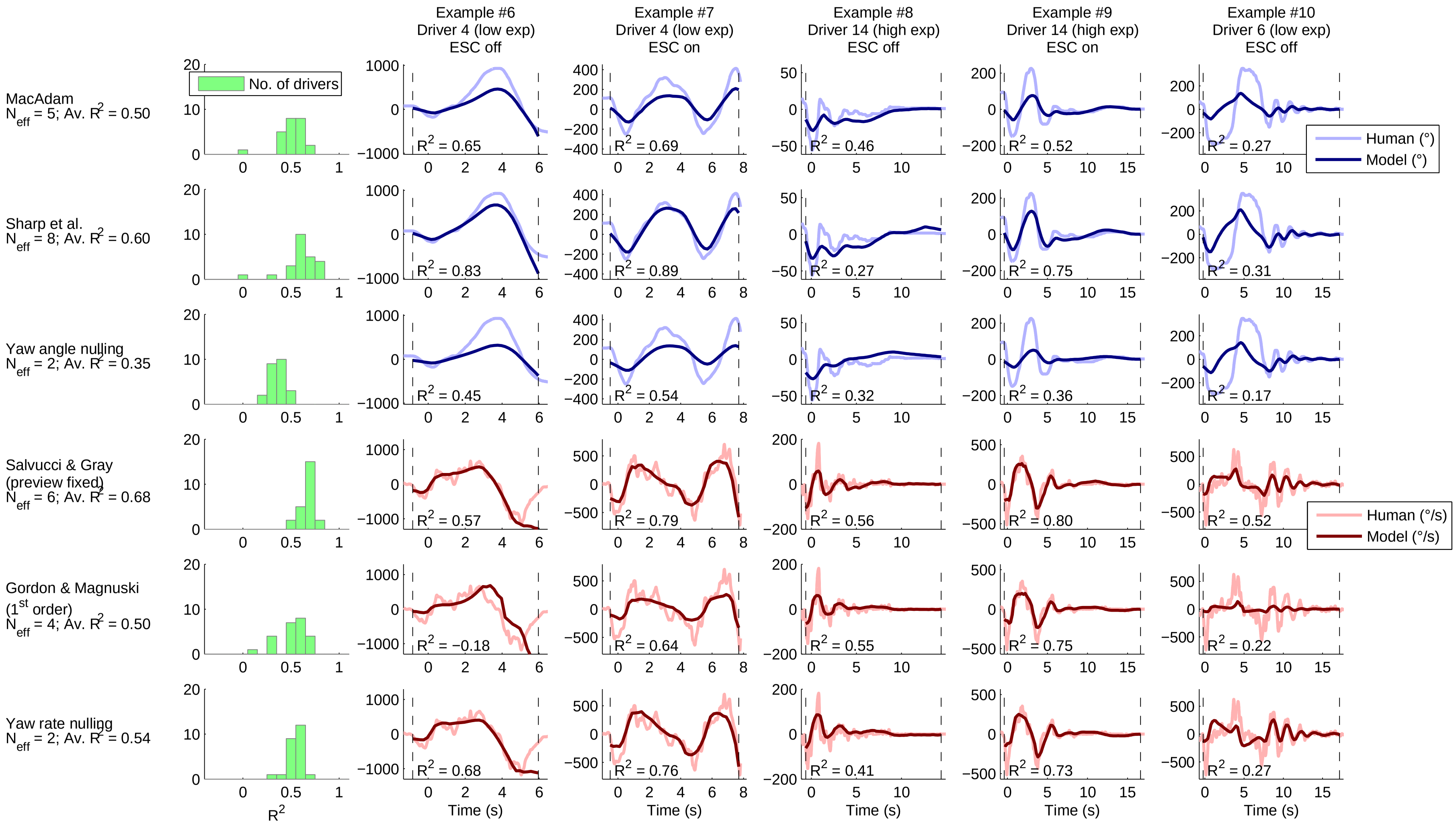


Figure 7. Stabilization steering. Distributions of average model performance (leftmost panels) and comparison of human and model steering in five example recorded scenarios, for six of the tested models. Besides including both novices and experienced drivers, driving with and without ESC, the example recordings have been chosen to illustrate typical model performance across various steering behaviours, and to highlight strengths and weaknesses of the different models. Note that the top three rows show models controlling steering angle (δ), whereas the bottom three show models controlling steering rate ($\dot{\delta}$), thus deviating somewhat from the order of model presentation in Sect. 2.2.

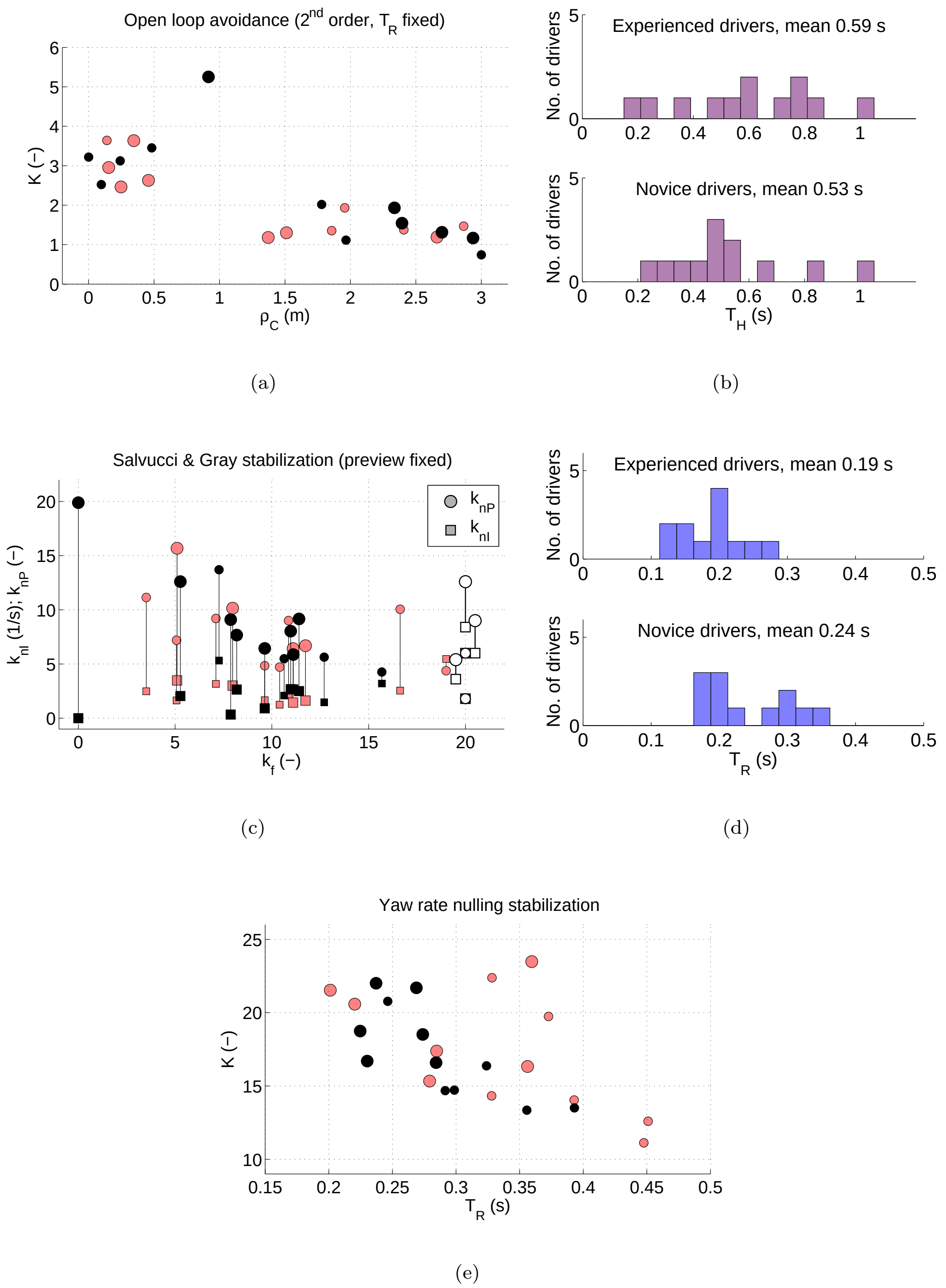


Figure 8. Obtained parameter values for the parameter-reduced variants of the open loop avoidance (panels (a) and (b)) and Salvucci & Gray (panels (c) and (d)) models, as well as for the yaw rate nulling model (panel (e)), for the 24 drivers in the data collection. In panels (a), (c), and (e), black symbols denote experienced drivers, and light red symbols denote novice drivers. Large and small symbols denote drivers for which average model R^2 was above and below the median value among the drivers, respectively. In panel (c), each driver is represented by a pair of one circle and one square, joined by a vertical line. The white symbols show parameterizations suggested for passenger car driving by Salvucci & Gray [37]; all of these are $k_f = 20$, but have been slightly displaced for clarity. In panels (b) and (d), distributions of model parameters T_H (the half-length of the open loop avoidance steering pulse) and T_R (the reaction time of the Salvucci & Gray model) are shown, separately for experienced and novice drivers.

4. Discussion

In general, the very simple open loop avoidance and yaw rate nulling models turned out to work rather well, and the performance of the more advanced models can to some extent be understood as being dependent on an ability to generate the behaviour of the simpler models. These aspects will be discussed below, separately for avoidance and stabilization. Before concluding, some remarks will also be made regarding the challenges involved in comparing and validating driver behaviour models.

4.1. *Collision avoidance*

4.1.1. Open loop avoidance steering

The open loop avoidance model provided the best fits of the human avoidance steering, both when comparing among models targeting δ and those targeting $\dot{\delta}$. Although there were cases where the human avoidance steering was more gradual (Example #1 in Fig. 6) or oscillatory (Example #5), in a majority of cases most of the total steering angle change was applied in a short period of time (Examples #2–#4), such as suggested by the correlation in Fig. 5(a). This type of open-loop account of collision avoidance steering is not new, and similar models have been used not the least in accident reconstruction work and *what-if* simulations [46–48].

The difference in fit between the constant and variable amplitude variants of the model (especially notable for the δ-controlling model; $R^2 = -1.20$ versus R^2 between 0.54 and 0.76) implies that drivers adapted their avoidance steering to the specific situation. The highest observed R^2 values (0.76 and 0.47, for the δ and $\dot{\delta}$ controlling variants, respectively) were obtained with the assumption that drivers selected their avoidance amplitude based on a 2$^{\text{nd}}$ order steering requirement prediction. This suggests that drivers may have been able to take the non-zero deceleration of the lead vehicle into account. On the other hand, the model variants based on looming, which does not include any acceleration information, reached almost as high R^2 values (0.71 and 0.46), so the results are far from conclusive in this respect.

When T_{R} was a free parameter in the optimizations, it varied throughout the entire permitted optimization interval of $[0, 2]$ seconds, something which could be interpreted as this parameter not being highly important for achieving a good fit, and this is confirmed by the very minor decrease in validation R^2 (from 0.76 to 0.75) when fixing T_{R} at 0.2 s. It is this parameter-reduced variant of the model which is the basis of Figs. 8(a) and (b). In (a), the correlation between ρ_{C} and K is clearly due to two clusters of parameterizations. These are interpretable, respectively, as (1) steering roughly as deemed necessary given the linear, low-friction vehicle model (K close to 1) to achieve what seems like an unrealistically large safety margin of about 1.5 – 3 m, and (2) steering aiming for a small safety margin of about 0 – 0.5 m, but applying a steering about three times larger than what the linear vehicle model predicts would be needed for this purpose. A possible interpretation of these fits is that the drivers adapted to the low friction circumstances, responding to vehicle understeering by applying larger steering angles than they would normally [23, 49]. Indeed, a separate, cursory analysis of the avoidance steering in the first, unexpected scenario suggests that while steering was predominantly pulse-like already at this point in the experiment (as implied also by Fig. 5(a)), the steering pulse amplitudes were generally smaller than predicted by the models fitted to the repeated-scenario data. To further clarify exactly how drivers select their avoidance steering amplitude, more data would be needed, from more varied kinematic situations.

With regards to the duration of avoidance steering (parameter T_H), Fig. 8(b) shows considerable variation between individuals, between 0.2 s and 1 s. The steering rate plots in the bottom three rows of Fig. 6 suggest that this is due to variations in the number of smaller steering corrections needed to achieve satisfactory collision avoidance (cf. [50]). It can also be noted that the average of 0.56 s shown in Fig. 8(b) is not far from the 0.42 s predicted by the slope of the correlation in Fig. 5. That these values are not exactly identical despite being estimated from the same data set is not surprising, if one considers the major differences between the two methods of estimation.

4.1.2. The other models of avoidance steering

In the cases where most of the steering wheel change occurred in a brief period of time (especially clear in Examples #2 and #3 in Fig. 6), the closed loop $\dot{\delta}$-controlling models by Salvucci & Gray and Gordon & Magnuski were less able than the $\dot{\delta}$-controlling open loop model at reproducing the resulting overall pulse of steering change. The closed loop models controlling δ (MacAdam and Sharp *et al.*) did produce the corresponding step-like δ outputs, but reached lower average validation R^2 than the $\dot{\delta}$-controlling open loop model, despite having a higher number of free parameters.

Besides lower R^2 values, another possible objection to the MacAdam and Sharp *et al.* models is related to their use of the desired path construct, which in the context of collision avoidance could be seen as problematic in at least two ways: (1) With a moving lead vehicle, the desired path will, during a first period of time, typically pass *through* the lead vehicle, which makes this construct less attractive than it may seem in scenarios where a path can be charted between stationary obstacles or lane boundaries. (2) There is a parameter redundancy by which an entire single lane change path (such as in this collision avoidance scenario) can be shifted longitudinally without affecting the steering behaviour, as long as one or both of the preview and reaction time parameters are appropriately modified at the same time. Besides these specific issues, it can also be noted that recent neurobiological models of basic sensorimotor control seem to be moving away from desired trajectory constructs, instead placing emphasis on *goal states* [51, 52], arguably more similar to the target lateral position of the Salvucci & Gray model or the Gordon & Magnuski model's goal of avoiding obstacles and lane boundaries.

4.2. *Stabilization*

4.2.1. Yaw rate nulling stabilization steering

When it comes to stabilization steering, it has been previously shown that models fitted to the repeated scenario data could successfully predict also unexpected scenario behaviour [32]. Here, the most important new result is the good fits obtained for the yaw rate nulling model. Given that the highest average validation R^2 across all stabilization models was 0.68, for the Salvucci & Gray model with six or eight free parameters (preview distances fixed or free), the R^2 of 0.54 yaw rate nulling model, with only two free parameters, seems very good. Qualitatively, the fits (such as shown in Fig. 7) are also rather convincing. The most natural interpretation of these observations seems to be that in the studied scenario, stabilization steering was indeed driven to a large extent by a control law similar to what the yaw rate nulling model suggests.

Three main types of cases were identified where the yaw rate nulling model did

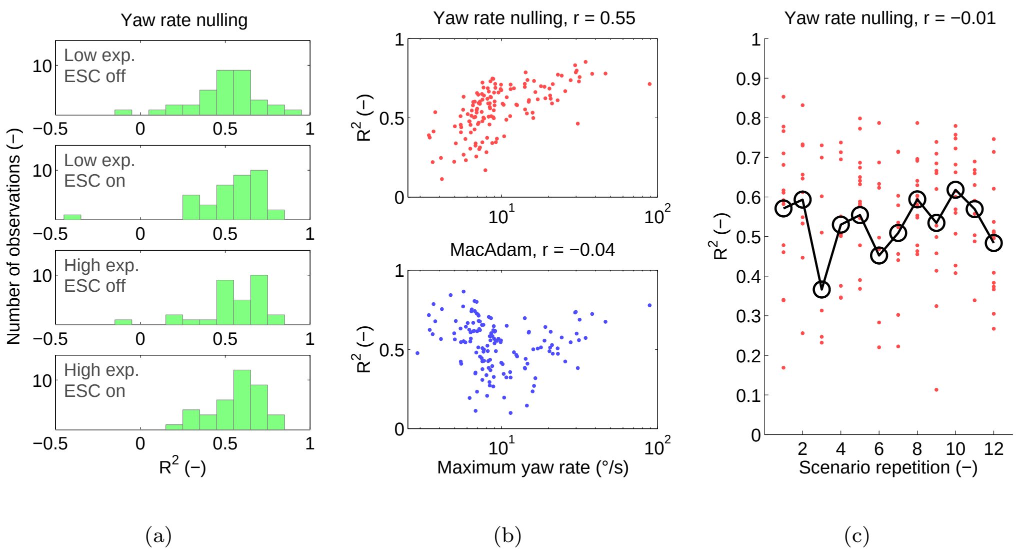


Figure 9. A more detailed view of model fits for the yaw rate nulling and MacAdam models, as a function of (a) experimental conditions, (b) maximum yaw rate attained during each scenario, and (c) scenario repetition. In panels (b) and (c), each small dot corresponds to one recorded scenario from the model-fitting validation set (three points with $R^2 < 0$ not shown for the yaw rate nulling model, two for the MacAdam model), and the r values are the corresponding Pearson correlation coefficients. In (a), the r values were calculated with the logarithm of the maximum yaw rates (such as shown here). Without the logarithms, $r = 0.40$ (top) and $r = 0.05$ (bottom). In (b), the rings are averages per repetition.

not work well: (1) Cases where the driver seemingly gave up steering in the face of imminent control loss (Example #6 in Fig. 7), possibly accounting to some extent for the left tails of the non-ESC distributions in Fig. 9(a), since control losses were more common without ESC [33]. (2) Cases with less vehicle instability and less critical steering (Example #8 in Fig. 7). Fig. 9(b) illustrates this phenomenon in more detail, by showing increasing model fits for increasing maximum vehicle yaw rates. (3) One or two novice drivers (including driver 6, see Example #10 of Fig. 7), who seem to have been using steering strategies of a qualitatively different kind, possibly accounting for the low-experience distributions in Fig. 9(a) being marginally farther to the left (combined average $R^2 = 0.52$) than the high-experience distributions (combined average $R^2 = 0.56$).

The pattern of lower steering gains K in drivers with longer reaction times T_{R}, shown in Fig. 8(e), can be interpreted as an adaptation of steering aggressivity to one's own response speed, to ensure vehicle stability. Such adaptation could have occurred as a learning effect during the experiment, but the lack of any clear effect of scenario repetition on model fit (Fig. 9(c)) rather suggests that drivers came to the experiment with this adaptation already in place.

4.2.2. The other models of stabilization steering

However, the yaw rate nulling model can hardly provide a full account of steering in the studied scenario; it can stabilize a vehicle directionally, but it has no means to make it stay on a road or close to some path. In contrast, all of the other tested models have such means, and all of them can also be made, more or less naturally, to exhibit some degree of yaw rate nulling.

The yaw angle nulling model will, by definition, have a steering rate of the yaw rate nulling form. Nevertheless, it provides rather poor fits of the human steering angle data (average validation $R^2 = 0.35$). This could possibly be due to the model's lack of a desired path or similar construct, making it unable to exhibit the rightward lane change during stabilization[1]. To keep the corresponding low-frequency component error down (e.g. in the second halves of Examples #8 and #9 in Fig. 7), the optimization may have favoured lower steering gains, in turn making the model unable to generate high-frequency steering of sufficient magnitudes during vehicle instability.

If so, the better fits of the Sharp *et al.* model (average validation $R^2 = 0.60$) could be due to its yaw angle nulling (the term in e_ψ) being relative to a desired path, but the lateral position error terms in the model may of course also have contributed. A main source of reduced R^2 values for this model seems to have been cases where the driver deviated from his or her own typical path in the scenario, such that the model's fitted desired path was not appropriate (Example #8).

The MacAdam model also has a desired path, but no direct means of applying yaw angle or yaw rate nulling. The fits obtained here had long preview times T_P (average 3.6 s, compared to 2.6 s for the Sharp *et al.* model). This makes the optimal control prioritize following the general direction of the road over correcting for local lateral position errors, in essence reducing it to the yaw angle nulling model, a similarity which is clear from Fig. 7. The resulting validation R^2 average of 0.50 was slightly lower than for the yaw rate nulling model, despite the larger number of free parameters, and there was no increase in model fit with increasing yaw instability (Fig. 9(b)).

The Gordon & Magnuski model, by Eq. (5), applies yaw rate nulling as long as $|\dot{\psi}_\mathrm{req}| \ll |\dot{\psi}|$. However, when close to a lane exceedence (Example #6 in Fig. 7) the model prioritizes lane keeping higher than the human drivers did. Overall, the model is also less aggressive in its yaw rate nulling behaviour than the humans (see the other examples in Fig. 7); possible reasons for this include the steering gains being kept down (the τ_s being kept high) to minimize error when yaw rates are low, and the model's satisficing approach of aiming for non-zero yaw rate remainders where the humans seemingly did not.

As shown mathematically in [32] and illustrated in Fig. 10, on a straight road far point rotation approximates negative yaw rate, such that the far point control of the Salvucci & Gray model can be understood as yaw rate nulling[1]. This insight helps explain the success of the Salvucci & Gray model in fitting the stabilization steering data, and also provides a candidate for a perceptual cue supporting yaw rate nulling behavior. However, the fact that the far point was parameter-fitted, here, to $D_\mathrm{f} = 123$ m ahead of the truck, whereas the 3° down from the horizon suggested by previous authors [37, 40] correspond to $D_\mathrm{f} \approx 50$ m for the truck in the experiment, could be taken to suggest that also other cues, such as vestibular cues [23] or large-field visual motion [55] may have been at play.

With regards to the other parameters of the Salvucci & Gray model, it is interesting to note the statistically significant faster response times for experienced drivers (Fig. 8(d)), in line with what has been suggested by several other authors; see e.g. [23] and [20, pp. 1132–1133]. The correlation between k_f and k_nP (Fig. 8(c)) could be understood as a parameter redundancy; one which is not surprising given the strong correlation between near and far point rates visible in Fig. 10. It is clear that with $D_\mathrm{n} = 16$ m, also the near point angle rate was a very close approximation of negative yaw rate, especially at low lateral speeds relative to the road. The exact values obtained here for k_f and k_nP should therefore not be attributed too much importance; they could simply be a more or less arbitrary division of the yaw rate nulling model's single gain parameter K.

[1]For studies of a yaw angle nulling model with a desired path, see [53] or [54].
[1]On a circular road, far point rotation nulling corresponds to nulling of yaw rate *error*.

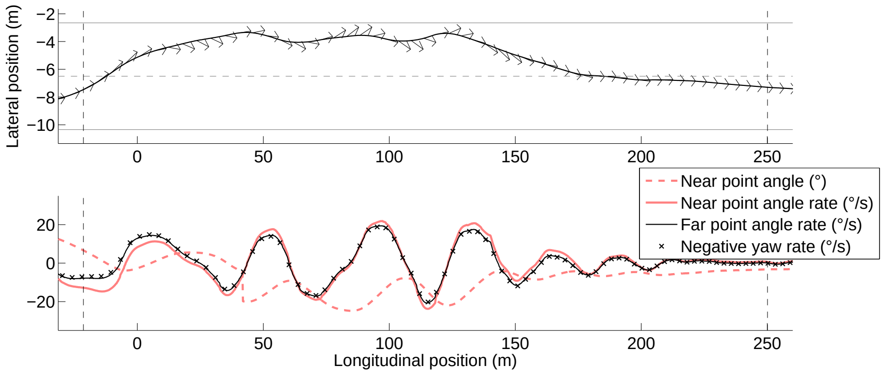


Figure 10. An illustration of the input quantities used by the Salvucci & Gray [37] model, in one example recording. The top panel shows the vehicle trajectory, including arrows showing momentary heading of the truck's front. The bottom panel shows the model input quantities, for $D_{\mathrm{n}} = 16$ m and $D_{\mathrm{f}} = 123$ m, as well as negative vehicle yaw rate. The discontinuity in the near point angle plot corresponds to the truck reaching longitudinal position X_3, where the model switches its target lane to the right. In both panels, longitudinal position zero corresponds to the point where the truck's front reached the rear of the lead vehicle, and the vertical dashed lines show the beginning and end of the stabilization phase as defined in Sec. 2.3.

4.3. *Comparing models of driver control behaviour*

One limitation in the comparisons presented here arises from some of the models predicting steering wheel angle δ, and others its time derivative $\dot{\delta}$. The differentiation from δ to $\dot{\delta}$ attenuates steering variations at low frequencies and amplifies those at high frequencies, which means that model-fitting to these two signals will put emphasis on different aspects of steering. For example, the δ and $\dot{\delta}$-controlling variants of the open loop avoidance model are logically equivalent, but the limitations of assuming a single burst of steering are more obvious in the $\dot{\delta}$ signal than in the δ signal, and this results in lower R^2 values for the $\dot{\delta}$ model variants. Indeed, none of the tested $\dot{\delta}$-controlling models include any input signals or mechanisms which could have allowed them to fully reproduce the type of high-frequency variations in $\dot{\delta}$ visible in Figs. 6 and 7.

Another limitation, here, is the informal treatment of model parameter count. In theory, additional model parameters cannot reduce model fit, only increase it, and will at the same time increase the risk of obtaining parameter values which overfit to regularities that are unique to the specific data set at hand (e.g. due to only considering one single driving scenario, such as here), thus potentially reducing generality of the parameter-fitted model. There are statistical methods for properly managing this trade-off between model complexity and model fit [56], but these are devised for probabilistic models, as opposed to the completely deterministic models considered here.

Because of the limitations outlined above, the results presented here do not provide grounds for a conclusive recommendation on what model or models to prefer for e.g. simulated evaluation of ESC. Leaving between-model R^2 comparisons to the side, an advantage of the Sharp *et al.* model is that it performed reasonably well both in avoidance and stabilization, implying that one could use a single model for an entire scenario. On the other hand, it could be argued that the Salvucci and Gray model seems more psychologically plausible, due to its input quantities being readily available to a human driver, and since it does not need to assume an internally planned desired path. Psychological plausibility may not be a major priority in some applied contexts, but could provide the benefit of a model that generalizes better beyond the specific data to which it has been parameter-fitted.

It should also be acknowledged, however, that while parameter-fitting of models

Table 2. A summary of advantages and disadvantages of the various tested models, in the studied low-friction collision avoidance scenario.

Model	Advantages in the studied scenario	Disadvantages in the studied scenario
MacAdam	Vehicle-independent parameters. Reasonable fit of avoidance steering.	Relies on desired path construct to achieve fit of avoidance steering. Rather poor fit of stabilization steering.
Sharp et al.	Reasonable fits of both avoidance and stabilization steering.	Relies on desired path construct. Many parameters.
Salvucci & Gray	Best fit of stabilization steering. Psychologically plausible input quantities.	Poor fit of avoidance steering. Rather many parameters.
Gordon & Magnuski	Psychological plausibility of satisficing approach.	Poor fit of avoidance steering and rather poor fit of stabilization steering.
Open loop avoidance	Best fit of avoidance steering.	Not applicable to stabilization steering.
Yaw angle nulling	Few parameters.	Not applicable to avoidance steering. Poor fit of stabilization steering. Not useful as a closed-loop model.
Yaw rate nulling	Reasonable fit of stabilization steering with few parameters, thus potentially indicative of a relevant behavioural phenomenon.	Not applicable to avoidance steering. Not useful as a closed-loop model.

such as performed here may be useful for understanding differences between models, and for pruning out models which do not work at all, it is not necessarily a suitable method for elucidating psychological mechanisms [57]. Here, the good fits of the yaw rate nulling model seem rather compelling, since this model has so few free parameters, but due to the parameter count effects discussed above, the higher R^2 values for the six-parameter Salvucci & Gray model should not be taken as *proof* of that model's underlying assumptions, e.g. that drivers are using near and far points to guide their steering. To study underlying mechanisms, a better approach is to instead identify situations where competing models diverge in their predictions about human behaviour, and then test these predictions in experiment [57].

In future model comparisons, to avoid the δ-$\dot{\delta}$ type of difficulty, one could consider fitting all models to the same control signal (e.g. $\dot{\delta}$). A study of closed-loop behaviour of the parameter-fitted models is also a natural next step, but has been beyond the scope here.

5. Conclusion

The work presented here has clarified some similarities and differences between a number of existing and novel models of driver steering. The strengths and weaknesses of these models in the specific studied scenario are summarized in Table 2. While it has been shown that several of the tested models were reasonably capable of reproducing the observed human steering behaviour, it also remains clear that, even within a well-defined and constrained context, it is non-trivial to decide which exact models to prefer over others. Furthermore, the poor fits reported here for some models do not imply that these models cannot work well in other contexts or scenarios. Especially regarding the Salvucci & Gray and Gordon & Magnuski models, it should be acknowledged that they were originally formulated for routine lane keeping, rather than near-limit manoeuvring.

Overall, model fits were not much affected by whether drivers were novices or experienced, or whether they were driving with ESC on or off. The drivers included here were all truck drivers, driving a simulated truck, but the simplicity of the main observed behavioural phenomena (open loop avoidance and yaw rate nulling stabilization) makes it reasonable to hypothesize that these phenomena could occur also in passenger car driving.

Regarding the general approach to modelling human control behaviour, the various models tested here are based on rather different underlying assumptions: From the MacAdam model that emphasizes an internalized model of vehicle dynamics and a desired path, to the Salvucci & Gray model that instead emphasizes visual cues allowing the driver to aim for a target lateral position. The results and analyses presented here show that these types of accounts can predict equivalent behaviour in some cases, but could diverge in others:

Collision avoidance steering was best described by the open-loop model, and the best-fitting version (average validation $R^2 = 0.76$) could be interpreted as the drivers acquiring an updated internal model of the vehicle's behaviour on the low-friction road. However, the version of the same model based instead on optical expansion of the lead vehicle on the driver's retina performed almost as well (average validation $R^2 = 0.71$), with one free parameter less.

Stabilization steering was explained to a large extent (average validation $R^2 = 0.54$), and especially well in recordings with more pronounced yaw instability, by the two-parameter yaw rate nulling model, according to which drivers apply a steering rate proportional to the negative of the vehicle's yaw rate. It is interesting to note that the Salvucci & Gray model (and to some extent also the Sharp *et al.* and Gordon & Magnuski models) clearly does predict a causation from instability to yaw rate nulling, due to sight point rotation nulling, and the Salvucci & Gray model also provided the highest average validation R^2 of 0.68 for the stabilization steering data.

The MacAdam model on the other hand, despite having more free parameters than the yaw rate nulling model, provided slightly worse fits of the stabilization data (average validation $R^2 = 0.50$, without a trend of better fits for more pronounced yaw instability). While, again, it is possible that better fits could be obtained by assuming that drivers acquired a more advanced, non-linear internal vehicle model [23, 49], compensating for tyre saturation with increased steering, it is presently not clear whether additional layers of assumed driver insight into vehicle dynamics would in the end really result in such a simply described, and seemingly non-optimal, behaviour as yaw rate nulling.

The fact that yaw rate nulling behavior during instability is correctly predicted by models originally devised for non-critical driving suggests the interesting possibility that drivers may be applying the same sensorimotor control heuristics (e.g. sight point rotation nulling) in both routine and critical situations (cf. [58]). By such an account, seemingly optimal, vehicle-dynamics-adapted behaviour from drivers in routine driving situations can be understood as these sensorimotor heuristics, although far from optimal in general, being precisely tuned for performance and efficiency after extended practice in a constrained operating regime. This would imply that modellers can afford themselves the practical advantages of optimal control theory and internal vehicle dynamics representations, when simulating driving situations of which the modelled driver has much experience (e.g. normal driving for normal drivers, race car driving for race car drivers). However, when modelling less frequent situations, such as traffic near-crashes, one may be better off with a model that is based on the underlying sensorimotor heuristics.

Acknowledgments

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Table A1. A listing of all model parameters included in the model-fitting optimizations. For each parameter, the allowed range in the optimizations is indicated, together with information on what models made use of the parameter, and on whether the model was considered effective in the collision avoidance and stabilization steering phases, respectively (i.e. whether or not it was included in the corresponding N_{eff} count in Table 1).

Parameter	Allowed range	Used by models[a]	Collision avoidance	Stabilization
ΔX_1	$[-50, 50]$ m	M, S	x	
X_2	$[-20, 30]$ m	M, S	x	
X_3	$[20, 70]$ m	M, S, S&G	x	x
X_4	$[100, 250]$ m	M, S, G&M		x
Y	$[-1.65, -6.5]$ m	M, S, S&G	x	x
T_{P}	$[0.1, 5]$ s	M, S	x	x
T_{R}	$[0, 2]$ s	M, S, S&G, G&M, OLA (except constant amplitude variant), YAN, YRN	x	x
K_{ψ}	$[0, 100]$	S	x	x
K_1	$[0, 100]$	S	x	x
K_{p}	$[0, 10]$	S	x	x
ΔX_{I}	$[-50, 0]$ m	S&G, G&M	x	
D_{n}	$[0.1, 200]$ m	S&G	x	x
D_{f}	$[0.1, 200]$ m	S&G	x	x
k_{f}	$[0, 100]$	S&G	x	x
k_{nP}	$[0, 50]$	S&G	x	x
k_{nI}	$[0, 10]$	S&G	x	x
ρ_{C}	$[0, 3]$ m	G&M, OLA (steering requirement variants)	x	x
ρ_{L}	$[-2.25, 3]$ m	G&M	x	x
τ_{s}	$[0, 10]$ s	G&M	x	x
K	$[0, 20]$	OLA (constant amplitude variant)	x	N/A
K	$[0, 200]$	OLA (other variants)	x	N/A
T_{A}	$[-0.5, 0.5]$ s	OLA	x	N/A
T_{H}	$[0.1, 1]$ s	OLA	x	N/A
K	$[0, 100]$	YAN, YRN	N/A	x

[a]M: MacAdam; S; Sharp *et al.*; S&G: Salvucci & Gray; G&M: Gordon & Magnuski; OLA: Open loop avoidance; YAN: Yaw angle nulling; YRN: Yaw rate nulling.

Appendix A. Genetic algorithm implementation

In the GA used for model-fitting (see Sec. 2.4), a candidate model parameterization was represented by a GA individual with a genome of length N, the number of free parameters of the model. Each gene was a floating point number in the interval $[0, 1]$, corresponding to a value within the allowed range for the parameter in question. These ranges are listed in Table A1, also showing which parameters were considered effective in the collision avoidance and stabilization phases, respectively.

The GA was configured, in the terminology and notation of [44, pp. 48–55], as follows: population size 100, tournament size 2, tournament selection parameter $p_{\mathrm{tour}} = 0.9$, crossover probability $p_{\mathrm{c}} = 1$, mutation probability $p_{\mathrm{mut}} = 1/N$. Mutation consisted in either (with probability 0.5) randomly choosing a new value from a uniform distribution in $[0, 1]$, or otherwise applying real-number creep from a normal distribution of standard deviation 0.005, after which the new value was bounded to $[0, 1]$. The best individual in a given GA generation was always retained in the next generation (elitism). Initial exploration indicated that model-fitting R^2 values were not very sensitive to the exact GA configuration, and the specific GA parameter settings adopted here were selected based on a criterion of low variability in R^2 estimates across repeated optimizations.

The GA was terminated at completion of generation number $2G$, where G was the last generation in the optimization with an increase in validation fitness. However, all optimizations were allowed a minimum of 300 generations.

Paper VI

Modeling driver control behavior in both routine and near-accident driving

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Modeling driver control behavior in both routine and near-accident driving

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Building on ideas from contemporary neuroscience, a framework is proposed in which drivers' steering and pedal behavior is modeled as a series of individual control adjustments, triggered after accumulation of sensory evidence for the need of an adjustment, or evidence that a previous or ongoing adjustment is not achieving the intended results. Example simulations are provided. Specifically, it is shown that evidence accumulation can account for previously unexplained variance in looming detection thresholds and brake onset timing. It is argued that the proposed framework resolves a discrepancy in the current driver modeling literature, by explaining not only the short-latency, well-tuned, closed-loop type of control of routine driving, but also the degradation into long-latency, ill-tuned open-loop control in more rare, unexpected, and urgent situations such as near-accidents.

INTRODUCTION

There is a wealth of existing models that describe the steering and pedal behavior exhibited by drivers to control their vehicles (Plöchl & Edelmann, 2007; Markkula et al., 2012). Such models can provide great advantages in many simulation-based approaches to the study of traffic, not the least concerning road safety (van Auken et al., 2011; Markkula et al., 2012). However, as will be described here in a brief literature review, driver models have so far taken rather different forms when accounting for routine driving behavior on the one hand, and near-accident behavior on the other. To date, there have been no models that predict the differing characteristics of control behavior in these two contexts, based on a single set of underlying assumptions. The aim of this paper is to present a framework which could be capable of doing so, partially with the help of some recent results from the neurobiological study of sensorimotor behavior. The argument for the proposed assumptions will be based on explanations of how the resulting framework is capable of predicting typical properties of both routine and near-accident behavior, complemented with reconsideration of some existing results from the driver behavior literature.

REVIEW

Most models of routine driving (Plöchl & Edelmann, 2007) assume that drivers engage in *closed-loop control*, continuously updating steering and pedals in response to the traffic situation, limited only by a constant *neuromuscular delay* of about 0.2 seconds. In contrast, typical models of near-accident control (van Auken et al., 2011; Kusano & Gabler, 2012) posit single *open-loop* braking or steering maneuvers of a shape that many closed-loop models have a hard time reproducing (Markkula et al., submitted), occurring after a long *reaction time* of about 1-2 seconds. Near-accident maneuver amplitudes have been modeled as basically random, with reports of both overreactions (Malaterre et al., 1988) and under-utilization of vehicle capabilities (Adams, 1994), whereas in routine driving, control has been assumed to be well-tuned to vehicle and situation dynamics, sometimes to the point of *optimal control*. Many routine driving models posit the use of *perceptual cues*, such as the movement of sight points for lateral control (Salvucci & Gray, 2004), or, for longitudinal control, the optical size θ and expansion $\dot{\theta}$ of a forward obstacle, the optically defined estimate of time to collision $\tau = \theta/\dot{\theta}$ (Lee, 1976; Flach et al., 2011) or its inverse $1/\tau$ (Kiefer et al., 2003). When such cues have been considered in near-accident control, it has been to discuss *detection thresholds*, the minimal stimuli at all discernible to a driver (Maddox & Kiefer, 2012). On the other hand, if thresholds have been applied in modeling of routine driving, it has mainly been to account for the *satisficing* nature of non-critical control: To limit expended effort, drivers postpone control until conflict-describing cues get large enough (Kiefer et al., 2003; Gordon & Magnuski, 2006; Flach et al., 2011), reaching levels orders of magnitude above typical thresholds for detection.

Considering the above, one could posit two distinct classes of behavior, mediated by different neural circuitry altogether. However, there are clear difficulties to this approach: Isn't there a continuum of traffic situations between "routine" and "near-accident"? And from where does the, albeit limited, near-accident ability of handling pedals and steering wheel come, if not from routine driving experience?

NEW CONTRIBUTION

Driving control as a series of open-loop adjustments

The first key assumption of the proposed framework is that, at a basic level, driving control is to a large extent

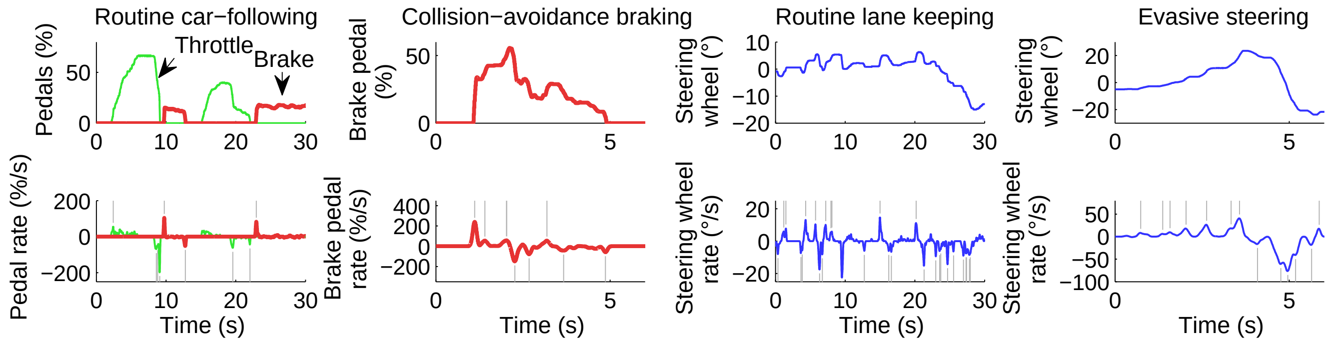

Figure 1. Example steering and pedal use in routine and near-accident situations, all from heavy truck driving in real traffic.

constructed from individual, discrete *control adjustments*, each of which is open-loop in the sense that the shape of the adjustment over time is predetermined already at its onset. Fig. 1 provides examples, from a data set of naturalistic driving, of human driving control in both routine and near-accident maneuvering. The lower row of panels show rates of change of pedal and steering wheel positions. These rates stay close to zero throughout, except for intermittent upward or downward pulses of activity (highlighted with vertical gray lines), interpretable as the hypothesized individual control adjustments. Previously, it has been observed that amplitude and maximum steering rate of severe evasive maneuvers are linearly correlated (Breuer, 1998; Markkula et al., submitted), suggesting a constant maneuver duration. Recently, Benderius and Markkula (2014) have shown that this correlation exists also for routine steering adjustments. These were found to follow bell-shaped profiles of movement speed, similar to what is consistently observed in laboratory experiments on reaching (Franklin & Wolpert, 2011). Short bell-shaped bursts of movement have been suggested to serve as spinal-level building blocks that can be combined and superpositioned to construct complex movement (Giszter, 2009).

It is proposed, here, that driving control adjustments are typically both small and frequent in occurrence, explaining why routine driving can nevertheless be well characterized as a continuous closed-loop activity. This would be especially true in situations like curve-taking (see the third panel from the left in Fig. 1, from about 20 s), where overall control is large in duration and amplitude, compared to the individual adjustments. However, in more urgent situations, where large changes in pedal or steering command are needed quickly, the underlying open-loop nature of control comes to the fore.

Additionally, when specific sequences of movement bursts are used recurrently, these can be established as higher-level movement primitives in their own right (Giszter, 2009). Such learning could be hypothesized for longer-duration control maneuvers that are recurrently useful in traffic, such as gradual changes in pedal position (visible for the throttle at 5 and 15 s in the leftmost panel of Fig. 1), intersection turning, or lane changes, which human drivers can perform blindfolded with some, but not complete, accuracy (Cloete & Wallis, 2009).

Some previous models of driving have considered intermittent control, occurring either at satisficing thresholds (Gordon & Magnuski, 2006) or as a result of bottlenecks in information processing (Bi et al., 2012). Here, another means of accounting for adjustment timing is adopted.

Timing distributions from noisy evidence accumulation

The second key assumption is that one needs to consider *distributions* of control timing, not only in near-accident control, but also in routine driving, and that these distributions are affected by, among other things, situation kinematics and expectancy. Specifically, it is suggested here that (a) late timing of control in unexpected critical situations and (b) satisficing timing of control in non-critical routine situations, are governed by the same underlying mechanisms.

A strong candidate for such a mechanism is available from *accumulator* models of action timing. These models, which assume that action occurs after integration to threshold of sensory evidence for an action's suitability, have been shown to account well for timing distributions in a large number of laboratory tasks, and through microelectrode recordings in behaving animals, likely neural correlates of this process have been identified (Purcell et al., 2010). Recently, Ratcliff and Strayer (2013) have successfully fitted this type of model to distributions of reaction time to one important fixed-intensity stimulus in traffic: brake lights.

In order to account for the satisficing patterns of behavior in routine driving, one would need to consider also variable-intensity stimuli, such as the perceptual cues used in many driver models. As a first indication that driver response timing can be understood as accumulation of such perceptual evidence, consider the experiment reported by Lamble et al. (1999), on how detection thresholds for optical expansion rate $\dot{\theta}$ vary with gaze eccentricity and initial lead vehicle headway: Test subjects, instructed to decelerate as soon as they detected a closing headway, consistently did so at lower $\dot{\theta}$ values for longer initial headways. This is precisely what would be predicted by an accumulator model where $\dot{\theta}$ is considered the stimulus intensity, since integration of a small quantity over a long time is equivalent to integration of a large quantity over a short time. To see this in more detail, consider the following simple accumulator:

$$\frac{dA(t)}{dt} = C \cdot P(t) - M + \varepsilon(t) \tag{1}$$

Where $P(t)$ is a stimulus, C and M are model parameters, and $\varepsilon(t)$ is noise, and where detection occurs when $A(t) \geq A_0$. This specific formulation is inspired by Purcell et al. (2010). In line with their interpretation of A as a neuron firing rate, this quantity is constrained to $A(t) \geq 0$.

The upper panels of Fig. 2 illustrate the behavior of this model, with $P(t) = \dot{\theta}(t)$, $C = 1$, and zero noise, parameter-fitted ($M = 0.000554$ rad/s; $A_0 = 0.00143$ rad) to reproduce the detection thresholds reported by Lamble et al. (1999) for zero gaze eccentricity. With a longer initial headway, $\dot{\theta}$ grows more slowly, meaning that A will reach threshold later in time, but at a lower final $\dot{\theta}$ value, just as observed in the experiment. The lower panels of Fig. 2 hint at how the same model could also account for the observed increasing thresholds and variance with increasing gaze eccentricity, by including a non-zero noise term $\varepsilon(t)$, and making C a nonlinear function of eccentricity (not pursued further here).

The experiment of Lamble et al. (1999) was not intended to approximate satisficing driver behavior. For a step in that direction, consider the results reported by Kiefer et al. (2003). These authors instructed drivers to wait to the last second deemed possible before applying “normal” or “hard” braking, in response to a set of test track scenarios with a lead vehicle mockup. This is also a rather artificial task, but arguably at least the normal braking condition could come somewhere close to routine, satisficing headway control. It is interesting to note, then, that the observed pattern of inverse times to collision (TTC) at response, in the normal-braking scenarios with lead vehicle deceleration, can be well explained ($R^2 = 0.91$) by an accumulator model with $P(t) = \dot{\theta}(t)/\theta(t) = 1/\tau(t)$; see Fig. 3 ($M = 0.00155$ s^{-1}; $A_0 = 0.0888$). For the scenarios without deceleration, on the other hand, the same model predicts a much earlier response than what was observed. This could mean that there is some fundamental flaw to the accumulator approach, but it could also be that the drivers were using some other perceptual cue than just $1/\tau$, or that the “last-second normal braking” task was further from routine driving behavior in the scenarios without deceleration.

In any case, in real traffic, driver behavior is not based solely on responding to graded perceptual quantities such as $1/\tau$. Fig. 4 provides an illustration of how Eq. (1) can be understood in this broader context. For example, braking may

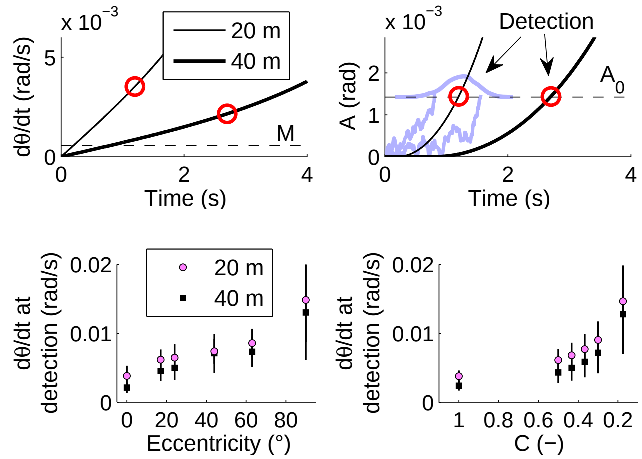

Figure 2. The 20 m and 40 m headway scenarios of Lamble et al. (1999). Top left: Growth of $\dot{\theta}$ over time. Top right: Accumulator model fitted to detection thresholds observed for zero gaze eccentricity, and illustration of model with noise (light blue trajectories and detection distribution). Bottom left: Detection thresholds (mean and standard deviation) as a function of gaze eccentricity, as observed by Lamble et al. Bottom right: Prediction from model with noise, at values of C selected to roughly match the data in the left panel.

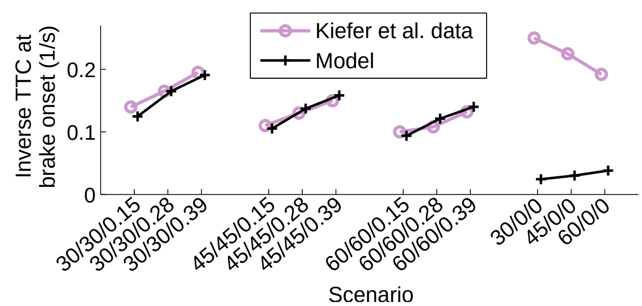

Figure 3. Accumulator model fit of “normal” last-second braking onset data from Kiefer et al. (2003), for decelerating and stationary lead vehicle scenarios (own speed in mph/lead vehicle speed in mph/lead vehicle deceleration in g).

be triggered without optical expansion, based on other evidence for its need, such as a brake light onset, or a red traffic light ahead of the lead vehicle. Conversely, braking may not occur despite optical expansion due to counter-evidence such as the traffic light shifting to green, or the lead vehicle’s turn indicator activating.

With Fig. 4 in mind, the perceptual quantity $P(t)$ in Eq. (1) can be interpreted as being one piece of evidence for a possible need of control adjustment, and the $-M$ term as being the sum of a negative gating (corresponding to a minimum level of input activation for accumulation to begin; again inspired

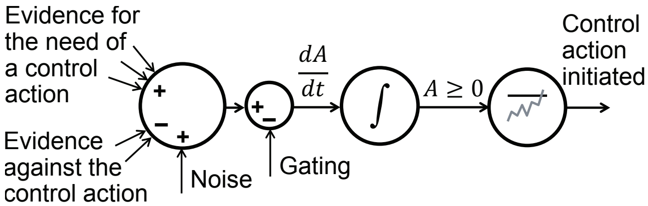

Figure 4. Schematic illustration of the proposed accumulator account of control adjustment timing.

by Purcell et al., 2010) together with all the other available evidence for and against the control adjustment. If so, the parameter M should vary with expectancy: In situations where the driver would normally not at all expect a need for a control adjustment, M will be larger, $\mathrm{d}A/\mathrm{d}t$ will be smaller, the driver will be correspondingly desensitized to the perceptual quantity P, and the time to response will be prolonged.

Magnitude of adjustments tuned to sensory inputs

Another important assumption, which may not be surprising given what has been said so far, is that the magnitude of each control adjustment is affected by the situation at hand. Specifically, it is suggested here that in routine, steady state driving, each control adjustment aims to resolve the situation that triggered it. A steering adjustment caused by a moving far point aims to immobilize the far point, a brake application caused by a looming lead vehicle aims to stop the looming. For often-encountered driving situations, drivers will have had ample time to learn suitable mappings from sensory input to control adjustment, acquiring a near-optimal trade-off between effort and performance, and what can be interpreted as a thorough understanding of their vehicle's dynamics. See (Markkula, 2013) for a sketch of how the far point control law suggested by Salvucci and Gray (2004) could be understood in this way. However, in more critical situations, typically previously unexperienced by the driver, the same mappings may no longer be as well-tuned to the situation or to the vehicle (Markkula et al., submitted), and this could explain reports of driver overreactions or underreactions in near-accident maneuvering. Furthermore, a possibly relevant neurobiological phenomenon in this context is *motor noise*, inherent variability in motor output which typically scales with movement amplitude (Franklin & Wolpert, 2011), such that large pedal or steering movements will be more likely to turn out far from what was intended by the driver.

Forward-model prediction of sensory input

An important follow-up question to what has been said so far is: When a control-adjusting burst of activity has been generated, how long time must pass before the next one can occur? To begin with, the previously cited work on motor primitives (Giszter, 2009) as well as Fig. 1 suggest that one does not have to await the completion of the first burst; control adjustments can be additively superpositioned. But if each control adjustment aims to completely resolve the situation that triggered it, such as suggested above, then superposition should not be needed. Rather, it would seem inappropriate to generate any further control until the vehicle has fully responded, with its inherent delays, to the first adjustment.

One possibility here is that the accumulator is simply reset to zero or some intermediate value after reaching threshold, and that during the time after the first control adjustment, when the original situation is still not fully resolved, the delays of the accumulation process in itself is enough to withhold further control response. A more elegant solution, with neurobiological support, would be that when the motor command for the first control adjustment is generated, an *efference copy* of this command is sent to parts of the brain (especially the cerebellum), which are capable of generating *forward model* predictions of the effect of the motor action on future sensory input (Franklin & Wolpert, 2011). It is thus proposed here that after each control adjustment, a prediction $P_p(t)$ is formed of how $P(t)$ will respond, e.g. by gradually falling to zero. $P_p(t)$ is then included as an inhibitory input to the accumulator, such that what is driving the accumulator is actually not $P(t)$, but $P(t) - P_p(t)$.

Fig. 5 illustrates the behavior of the brake reaction model fitted to the Kiefer et al. (2003) data (Fig. 3), complemented with (a) a linear mapping from $1/\tau$ at brake adjustment onset to adjustment amplitude, well-tuned for moderate levels of lead vehicle braking, and (b) a simple forward model of how $1/\tau$ will respond to such adjustments. Full details of these simulations are beyond the scope here; they are shown merely as a qualitative illustration of the proposed framework principles. Specifically, it can be noted how an unusually high lead vehicle deceleration causes an initial underreaction, followed by increases in pedal position later on.

DISCUSSION

Many testable predictions can be made based on the framework proposed here. For example, in both routine and near-accident situations, control timing should be affected by the dynamics of both traffic situation and evidence accumulation, such as preliminarily suggested here for the Kiefer et al. (2003) data set. To test this prediction in more detail, controlled experiments are needed, where situation dynamics are varied while keeping constant any other evidence to the driver for or against the need of control adjustments.

If the suggested framework principles can be corroborated, they can be used for developing improved simulation models of driver behavior. Near-accident models can be extended with situation-dependent distributions for both response time and maneuver amplitudes. Routine driving

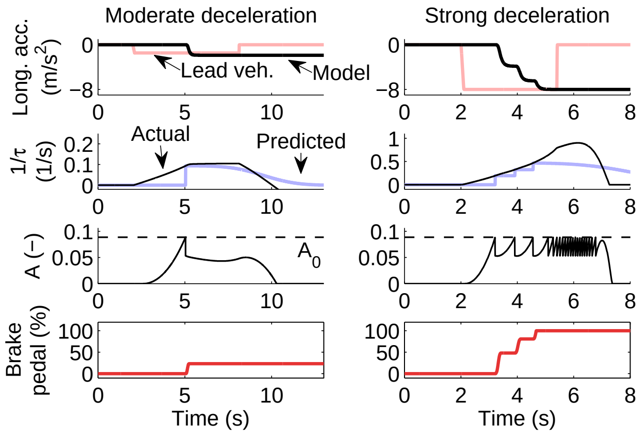

Figure 5. A braking model based on the proposed framework, in two scenarios with lead vehicle deceleration.

models can be extended to better account for control, most immediately in situations where longer-duration learned maneuvers should be rare, such as keeping in a lane with low curvature, or car-following at roughly constant speed.

It should be noted that several factors important for driving control have been left out of the scope here, such as arousal, cognitive control, and sensorimotor learning (Engström et al., 2013). However, the proposed framework seems highly amenable to extensions in these directions, probably more so than alternative frameworks based on for example control theory.

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