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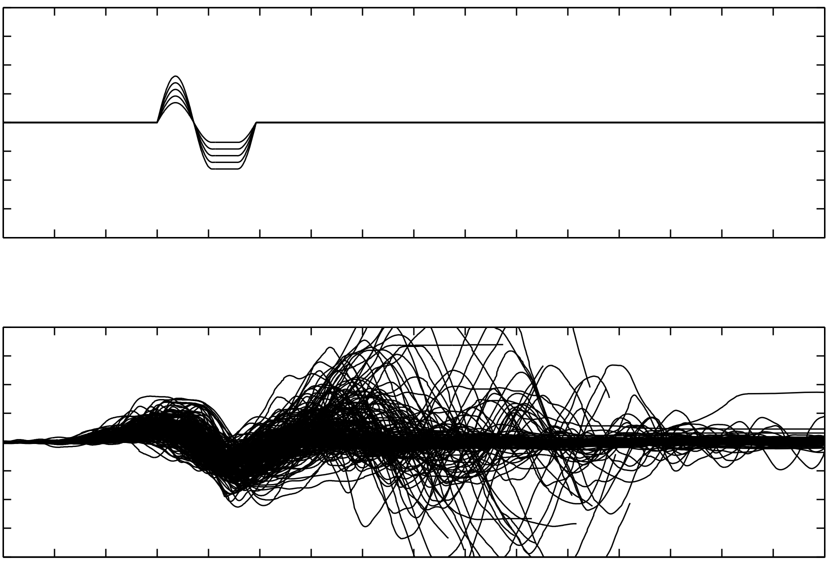

Evaluating vehicle stability support systems by measuring, analyzing, and modeling driver behavior

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Department of Applied Mechanics
CHALMERS UNIVERSITY OF TECHNOLOGY

Gothenburg, Sweden 2013

Thesis for the degree of Licentiate of Engineering

in

Machine and Vehicle Systems

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THESIS FOR LICENTIATE OF ENGINEERING no 2013:11
ISSN 1652-8565

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Cover: Both panels show steering wheel input (unit: 180°) as a function of time (unit: 1 s). The upper panel shows four different amplitudes of the standardized *sine with dwell* steering maneuver, often used in test track-based evaluation of electronic stability control (ESC); see page 6. The lower panel shows the totality of all *ESC-relevant* steering behaviors observed in a repeated collision avoidance scenario described in this thesis; see page 18.

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Evaluating vehicle stability support systems by measuring, analyzing, and modeling driver behavior

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Abstract

This thesis presents an investigation of near-accident behavior of truck drivers, with and without support from an electronic stability control (ESC) system. A critical scenario, involving both collision avoidance and vehicle stabilization on a low-friction surface, was studied in a driving simulator. The simulator experiment included a novel experimental paradigm, in which several measurements of critical maneuvering were generated per test subject.

In this paradigm, ESC was found to provide statistically significant reductions of skidding and control loss, and the drivers were found to employ similar strategies for steering control as when they experienced the same scenario unexpectedly. These findings imply that the system should provide stability improvements also in unexpected maneuvering, something that has not been previously demonstrated for heavy truck ESC.

A review of existing driver behavior models that can be used in simulation-based testing of active safety systems (such as, for example, ESC) is also presented. The review showed that, while a wide range of models has been proposed, the generated behavior can sometimes be more similar between models than what the model equations may suggest. Validation of models on actual near-accident behavior of real drivers has so far been very limited.

Here, it is shown that an existing model of steering can reproduce the stabilization steering behavior observed in the simulator study. It is also demonstrated how this model can be mathematically linked to vehicle dynamics concepts, increasing its usefulness in applied contexts.

Keywords: Active safety, electronic stability control, heavy trucks, system evaluation, driving simulators, driver behavior, driver models

Acknowledgements

Thesis work is a lengthy process, and even if I'm so far only halfway to the final goal, thanks are already due to many people:

To friend and fellow PhD student Ola Benderius, for our fruitful discussions and your most agreeable company. Likewise, to friends and colleagues Johan Engström, Emma Johansson, Trent Victor, and Johan Lodin.

To Kristoffer Tagesson, Niklas Fröjd, Stefan Edlund, Leo Laine, and Nicolas Dela, for continuously taking the time to keep one of my feet firmly planted in the applied reality of heavy trucks and their stability, such that the other foot can freely do its tap dancing around among the obscurest of neuroscientific literature.

To Lars Eriksson, Anne Bolling, Jonas Andersson Hultgren, and Anders Andersson, for your indispensable support in preparing and conducting the driving simulator study.

To supervisors and managers Dr. Mattias Wahde, Dr. Krister Wolff, Dr. Hans-Erik Pettersson, Peter Wells, Dr. Lennart Cider, Joakim Svensson, and Helene Niklasson, for your time, your most insightful guidance, and not the least for your sound priorities, thanks to which I believe I so far *don't* need to thank my other friends, my family and, especially, my wonderful girls, Veronica and Charlotte, for their enduring patience with my work.

(Everything else, of course, is and always will be thanks to them.)

List of included papers

This thesis consists of the following papers. References to the papers will be made using Roman numerals.

I. Markkula, G., Benderius, O., Wolff, K., and Wahde, M., *Effects of experience and electronic stability control on low friction collision avoidance in a truck driving simulator.* Accident Analysis and Prevention 50, pp. 1266–1277, 2013.

II. Benderius, O., Markkula, G., Wolff, K., and Wahde, M., *Driver behaviour in unexpected critical events and in repeated exposures – a comparison.* Submitted to European Transport Research Review.

III. Markkula, G., Benderius, O., Wolff, K., and Wahde, M., *A review of near-collision driver behavior models.* Human Factors: The Journal of the Human Factors and Ergonomics Society 54(6), pp. 1117–1143, 2012.

Related publications by the author, not included in the thesis: [5,13,19,60–62]

Technical terms used in the thesis

Table of Contents

Chapter 1

Introduction and motivation

Any adult individual in modern society is well aware that road traffic occasionally leads to accidents, causing economic costs, injuries and sometimes even death. Most would agree that this is a serious problem, but exactly *how* serious is it? One can take at least two perspectives when answering this question, both highly relevant, but in a sense leading to different answers.

From a global or societal perspective, road safety is a major challenge. In 2004, more than one million people died in vehicle crashes, making road traffic accidents the ninth most common cause of death, worldwide, and the predicted ranking for 2030 is a fifth place [99]. Counting both fatalities and injuries, costs for crashes are estimated to amount to 1-3 % of countries' gross domestic products [100].

However, from the perspective of the individual driver, accidents are very 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 [69]. Given such figures, one must admit that the average driver is impressively proficient at avoiding crashes.

This can to some extent seem odd, since it is also well established that when road traffic accidents do occur, human behavior almost always plays an important role, in the form of for example inattention, excessive speeding, or inadequate evasive maneuvering [50, 87]. Furthermore, 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 [6, 37, 38].

As with any technology, active safety systems need **evaluation**, in order to determine to what extent they fulfil their intended purpose of reducing frequency or severity of crashes. System developers need to carry out **formative** evaluation [55], 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 [55] 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 the low-level, driver perspective highlights a possible difficulty in their evaluation. 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 studying behavior in near-accident situations, and creating mathematical models describing it. Such driver behavior models can, for example, allow active safety evaluation based on computer simulation of relevant crash scenarios [8, 82]. In order to maintain a manageable scope of behaviors to study and model, this thesis focuses on evaluation of **electronic stability control (ESC)** for heavy trucks, in one specific accident scenario.

The remainder of this chapter provides brief introductions to ESC systems, the general state of knowledge with regards to driver behavior in accident situations, and existing methods for evaluation of active safety. At the end of the chapter, the main research questions and the general research approach are introduced, and an outline is provided for the rest of the thesis.

1.1 Electronic stability control

In normal driving, a road vehicle travels roughly in the direction in which its front wheels are pointing, with close to horizontal alignment (zero pitch and roll angles). Any departures from this normal state are typically only temporary, thanks to stability properties of the vehicle, or corrective responses from the driver. However, in some situations, deviations from the normal state may increase in magnitude, either monotonously or in an oscillatory fashion, and then **vehicle instability** can be said to have occurred [27]. Typical examples include high speed driving in curves, leading to roll-over (**roll instability**), or steering maneuvers beyond what is feasible given the available friction between road and tires, causing skidding (**yaw instability**).

The ability of human drivers to prevent or counteract such instabilities

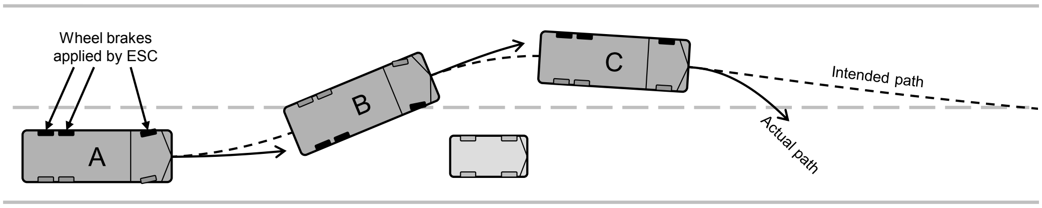

Figure 1.1: *Schematic illustration of typical yaw stability control interventions of the electronic stability control (ESC) system of a rigid truck, during a collision avoidance maneuver on a low friction road surface. A and B are examples of understeering, where the low friction causes the truck to turn less than intended by the driver. In C, the built-up rotation of the truck insteads leads to oversteering. In all three cases, ESC applies braking at individual wheels to achieve the intended motion. (See e.g. [84].)*

is limited by, at least, neuromuscular reaction times and movement speed limitations [58], a lack of sensory input regarding the exact state of the vehicle and its individual wheels, and rather blunt means of control (steering wheel and pedals, mainly). ESC systems, on the other hand, are designed not to have any of these limitations, and may include sub-systems both for **roll stability control (RSC)** and **yaw stability control (YSC)**.

An RSC system typically estimates the lateral acceleration of the vehicle, and slows the vehicle down if a risk of roll-over is detected [70, 98]. A typical YSC system works by comparing the current lateral movement or rotation of the vehicle to what seems to be the intention of the driver, based on current steering wheel input, and applies individual wheel brakes to achieve the desired vehicle movement [84, 91]. Fig. 1.1 illustrates how YSC systems may respond to **understeering** and **oversteering** of a rigid heavy truck (as opposed to an articulated heavy truck, such as a tractor-semitrailer combination) during collision avoidance and subsequent stabilization, which is precisely the type of scenario studied in this thesis.

From 2014, an ESC system such as the one outlined above will be mandatory in all new heavy trucks in Europe [22]. Based on in-depth accident studies, it has been estimated that 19 % of all heavy truck crashes in the U.S. in 2001-2003 could have been prevented or mitigated by ESC [43].

1.2 Driver behavior and traffic accidents

How can one understand and describe behavior such as, for example, the behavior exhibited by the truck driver in Fig. 1.1? On the conceptual level, there is a wealth of theories and models that propose different ways of how

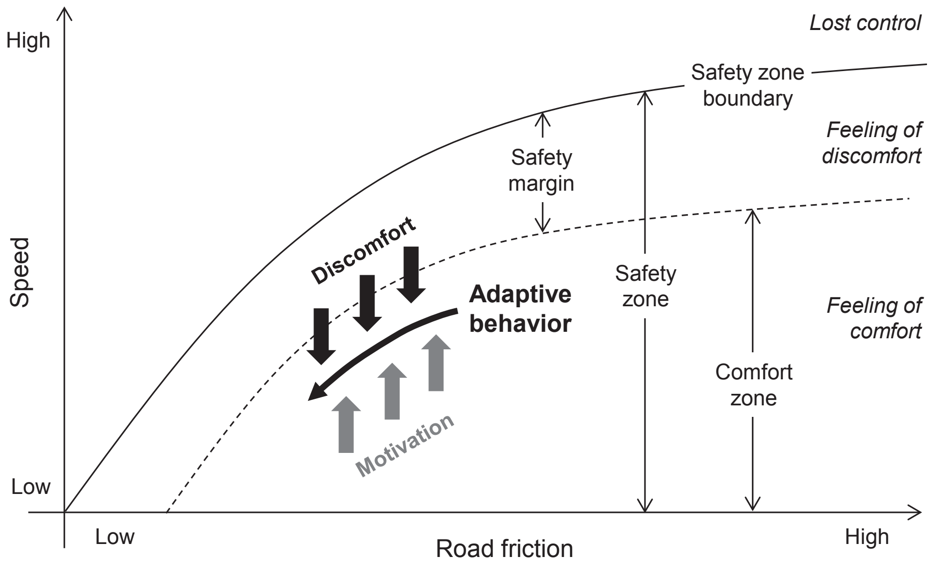

Figure 1.2: *Illustrations of key concepts of the conceptual framework of Ljung Aust and Engström, in a hypothetical scenario where a driver perceives a drop in road friction, and thus reduces vehicle speed to avoid experiencing feelings of discomfort. After [56].*

to best discuss driving, and sometimes also accidents [19, 65, 83, 90]. Here, a conceptual framework proposed by Ljung Aust and Engström [56], 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** 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 point 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 (1) erroneous perception of the current safety zone boundary, (2) overestimation of the ability of oneself or of the vehicle, (3) an incorrect prediction of how a situation will develop over time, and (4) 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 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 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 [12,20,46] or personality [85], or within a given driver depending on, for example, factors such as fatigue [3] or effort [16,75].

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 [31,33,74]. 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. In realistic or real near-crash situations, drivers often exhibit a number of non-routine behaviors, such as unusually slow reactions, or no reactions at all, even to stimuli that would seem to motivate immediate reactions [30,52,95]. 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 [2,49], or may come in the form of overreactions [59,98] or underreactions not utilizing the full performance capabilities of the vehicle [2,44,49]. Some of the main candidates for factors explaining such behaviors 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 [7,14,30,49].

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?

1.3 Evaluation of active safety functions

Arguably, the only way of evaluating active safety that is completely valid, from a driver behavior perspective, is to consider only **naturalistic** situations, as in real critical situations, in real traffic. The most straightforward approach to doing so is to use accident statistics: 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. In this way, passenger car ESC has been reliably shown to prevent about 40 % of all crashes involving loss of control [36].

A related approach, yielding more rich data sets, and 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 normal drivers during extended periods of time [4,42]. One clear limitation with this type of approach is the high cost. Furthermore, no FOTs known to the author have targeted ESC. In addition, a necessary limitation of any naturalistic evaluation approach is the requirement of having system hardware and software at a maturity level that is sufficient for prolonged use by end-users. In practice, this means that naturalistic evaluation will typically 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, typically using experienced test drivers or driving robots. This is a frequent approach to ESC evaluation, and a number of different predefined **open-loop** steering wheel inputs[1] or vehicle paths to follow have been proposed for eliciting the types of vehicle instabilities targeted by ESC systems [43,54]. A main benefit of such evaluation is the relatively high **repeatability**, allowing efficient comparison of the stability performance between alternative versions of an ESC system, or between different ESC-equipped vehicles. Consequently, this is also the approach used for type approval and safety rating of on-market ESC [21, 22, 89].

However, it should be acknowledged that much realism in driver behavior may have been sacrificed in order to reach this repeatability. It would seem likely that steering robots executing predefined 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. Furthermore, it would presumably 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

[1] The much used **sine with dwell** maneuver [47,89] is shown on the cover of this thesis.

not to say that ESC systems evaluated on the test track do not provide real benefits for traffic safety (as mentioned above, at least for passenger cars it is clear that they do), but it could for example mean that a better performance of ESC system A than ESC system B in a test track evaluation does not guarantee that system A will provide the greater benefit in reality.

A kind of middle ground between naturalistic evaluation and test track evaluation is offered by **driving simulators**. In driving simulation, 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. A series of large simulator experiments (up to two hundred subjects per experiment) on passenger car ESC have been carried out at the U.S. National Advanced Driving Simulator (NADS) [63, 72, 73, 94], showing significant reductions in loss of control crashes with ESC.

To the author's knowledge, there has been only one prior simulator study on truck ESC [13]. This study failed to show a benefit of truck ESC, possibly because of a too small sample of ESC-relevant maneuvering. Indeed, since considerable behavioral variability typically occurs in simulator-based evaluation, any two measurements cannot readily be compared to each other (such as they can, to a greater extent, on the test track), and large numbers of measurements are therefore often needed in order to statistically confirm any system effects. Consequently, cost is definitely also a concern in evaluation with driving simulators, especially since driver expectancies for critical situations typically increase with exposure, making it difficult to validly record near-crash behavior more than once per subject [17].

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. This benefit of computer simulation as an evaluation tool is well appreciated by ESC developers and researchers, but so far the approach has generally been to simulate the same predefined low-variability scenarios as on the test track, rather than realistic near-crash scenarios [43, 64, 98, 101]. For other active safety systems, such as systems warning or intervening in the case of lane departures or rear-end collisions, there is a number of examples in the literature of simulation-based evaluation aiming at reproducing realistic situations [8, 24, 29, 45]. However, the only two ESC evaluations of this kind known to the author [15, 66] were based on driver models that in one case could only exhibit open-loop behavior [81], and in neither case seem to have been validated on human behavior in critical situations [53, 81].

1.4 Research questions and approach

As mentioned above, the general aim of the research work presented in this thesis has been to create models that accurately describe behavior of drivers in near-crash situations, in order to allow active safety evaluation based on computer simulations.

The specific research questions addressed in this thesis are: (A) Does heavy truck ESC provide a safety benefit to normal drivers in realistic near-crash scenarios? (B) Is ESC more useful for some drivers than for others? Both of these questions currently seem to be open, and the general approach to attempt answering them has been to:

(i) Collect data on behavior of normal drivers in realistic near-crash situations.

(ii) Provide as complete answers as possible to the research questions, by means of conventional statistical analysis of the obtained behavior data.

(iii) Develop mathematical models which can reproduce the observed driver behavior.

(iv) Carry out computer simulations with these models, to make it possible to answer the research questions in more detail.

1.5 Contributions and thesis structure

This thesis addresses (i) and (ii) above, data collection and statistical analysis, in Chapters 2 and 3, respectively. The author had the main responsibility for the design of the data collection experiment, the basis of both Paper I and Paper II. The author also carried out the statistical analyses reported in Paper I, and was responsible for most of the writing. The author collaborated with Benderius in determining the analysis approach for Paper II, and assisted in the writing.

Chapter 4 of the the thesis partially addresses step (iii), on driver modeling. This includes a summary of the literature review reported in Paper III, which the author prepared and wrote in collaboration with the other authors.

An overall discussion is provided in Chapter 5, including outlooks on the work done to fully address steps (iii) and (iv). This work remains to be described in forthcoming publications. Final conclusions are provided in Chapter 6.

Chapter 2

An empirical study of critical maneuvering

As discussed in the introductory chapter, driving simulators can strike a reasonable balance between scenario realism on the one hand, and measurement repeatability on the other. Data for this research were collected in *Driving Simulator II*, a moving-base simulator at VTI (Swedish National Road and Transport Research Institute) in Linköping, into which Volvo Trucks' on-market ESC system had been integrated. Driving experience, known to have considerable effects on driving behavior and safety [12, 20, 46], was adopted as a controlled source of behavioral variability, and a total of 48 subjects were recruited into one novice group, from a local truck driving school, and one experienced group (4-43 years of professional driving), from local hauler companies.

Full technical details on the study are available in Paper I. This chapter provides a summary, but also aims to give additional insights into the process leading up to the final study design, a process that required consideration of several challenging questions: How does one get a professional driver into a situation where he or she may lose control of the vehicle? How can the amount of collected data be maximized within the budget limitations of the experiment? Is it possible to design a scenario in which drivers repeatedly engage in the same type of maneuvering as in an unexpected scenario?

2.1 Selecting a simulated scenario

The choice of a critical scenario was based on three main factors: (a) traffic safety relevance, given available accident statistics, (b) the degree to which the scenario could be expected to lead drivers into the intended vehicle instabilities, and (c) the expected usefulness of an increased understanding of driver behavior in the scenario.

Roll instability is more common in heavy truck crashes than yaw instability [43, 92]. In the U.S., 55 % of control loss crashes in 2001-2003 involved roll-over, 31 % involved loss of yaw control, and the rest (14 %) involved both [43]. The typical pre-crash scenario for roll-over accidents was curve negotiation with excessive speed. For yaw control loss crashes, the same study found the most common scenarios to be curve negotation (36 %), collision avoidance maneuvers (22 %), and heavy braking (22 %).

However, the previous study on truck ESC by Dela *et al.* (including the author of this thesis) had been unsuccessful at getting truck drivers into roll instability, despite using a scenario with an unexpectedly narrowing curve [13, 62]. Furthermore, it was judged that the room for variability in driver behavior, a main subject of this thesis, would be smaller in a high-curvature scenario, both at high friction (roll instability) and low friction (understeering yaw instability), than in a low-friction scenario capable of generating oversteering yaw instability. Therefore, a study of realistic driver behavior in an oversteering scenario was considered more valuable, with a greater potential of providing a clear step forward from existing test track evaluation methods and driver models.

Dela *et al.* [13] investigated a number of relevant scenarios capable of inducing oversteering. A couple of these were similar to scenarios used in the NADS studies on passenger car ESC [63, 72, 94], featuring obscured and suddenly appearing vehicles intended to motivate vigorous evasive maneuvers. However, preliminary tests by Dela *et al.* indicated that these scenarios did not work as expected in the truck context, since the truck drivers exhibited highly successful adaptive behavior: Already at the first encounter with the scenarios, the drivers updated either lateral position or speed enough to maintain sufficient safety margins to any appearing vehicles. Therefore, Dela *et al.* adopted a scenario where no such anticipatory adaptation was possible: a moose suddenly crossing the road. A main limitation of this scenario was that many drivers did not at all steer to avoid the moose, and according to some of the truck drivers this reflected a strategy of preferring an animal collision over heavy lateral maneuvering.

Based on these prior experiences, the final choice, here, fell on the scenario depicted in Fig. 2.1. In this scenario, originally proposed by Engström *et al.* [18], an overtaking higher-speed vehicle suddenly brakes for no apparent reason, causing a risk of rear-end collision This scenario has two main strengths: (a) It features another human road user rather than an animal, presumably reducing truck driver willingness to accept collision as a viable

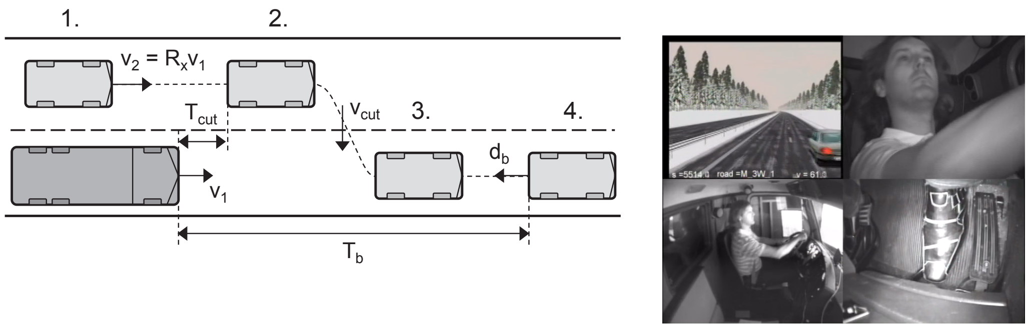

Figure 2.1: ***Left:*** *Illustration of the critical scenario studied in this thesis, adopted from [18]. A higher-speed passenger car (1) overtakes the truck, and at preset time headways first (2, 3) cuts into the truck's lane, and then (4) starts braking, for no apparent reason.* ***Right:*** *A still from the recorded video data, showing the winter environment in which the simulated avoidance scenario took place, and a driver engaged in steering avoidance.*

option. (b) It plays on the truck driver having a (highly reasonable) expectation for the higher-speed car to drive away into the distance, reducing the probability of safety margin-increasing adaptations [17].

Here, the scenario took place on a winter highway, with two lanes in the truck's driving direction, thus leaving room for a steering collision avoidance to the left of the braking lead vehicle. Just before the lead vehicle started braking, road friction was changed, without any visual indication to the truck driver, from $\mu = 0.8$, emulating a dry road surface, to $\mu = 0.25$, emulating a wet or icy road surface.

2.2 Maximizing the amount of collected data

Simulator-based evaluations of active safety systems often begin as follows [17,18,51,73]: (a) Let the subjects get accustomed to the simulator, by means of a training drive. (b) Then, instruct subjects to drive as usual, and do not mention anything that could heighten expectancy for critical situations. (c) After a while, trigger an unexpected critical situation, in which half of the subjects are supported by the active safety technology, and the other half are not. Such a procedure was adopted also in this experiment.

As mentioned above in Chapter 1, going beyond such a minimal approach, and subjecting drivers to more than one critical situation may, in general, raise validity concerns. Furthermore, it was expected that if the specific scenario adopted here were to be repeated more than once per driver, behavioral adaptation such as witnessed by Dela *et al.* would quickly render the scenario non-critical. However, only collecting one measurement per subject would have been problematic, since it was not possible to involve hundreds of subjects (in order to increase chances of observing statistically significant effects of ESC). Also, discerning potential driver-specific behavior styles on the basis of a single measurement per driver seemed difficult, if not impossible. Therefore, two extensions were made to the study, to allow collection of additional data.

The first extension was the development of an instruction-based paradigm for **repeated collision avoidance**, more similar to a typical psychology experiment than a typical active safety experiment. After the first, unexpected occurrence of the critical scenario, drivers were informed of the slippery road condition, and of the presence or absence of ESC in their truck. This information was given to avoid unwanted behavioral variability, caused by drivers possibly deducing the same information themselves, gradually and at an individual pace. Furthermore, drivers were told that they should now continue driving as before, that cars would continue to overtake them and sometimes brake in front of them, but that in a majority of cases, braking the truck without steering would be sufficient to avoid the collision. In cases where braking would be insufficient, the truck drivers were instructed to try to avoid the collision by steering. In practice, this experimental situation was achieved by interspersing repetitions of the critical scenario with a **catch trial** scenario, in which the lead vehicle only decelerated for a limited time (down to a speed v_3), and then instead applied a large forward acceleration.

This paradigm acknowledges the fact that repetition of near-crash events will have effects on driver behavior. What it attempts to achieve is a situation where all drivers quickly reach the same expectancies, where multiple measurements of behavior in the scenario can be made per driver, and where at least the steering behavior can potentially be comparable between unexpected and repeated scenarios. The top half of Fig. 2.2 illustrates the full experimental sequence, allowing recording of one unexpected and twelve repeated instances of collision avoidance for each driver.

The second extension, illustrated in the bottom half of Fig. 2.2, was the inclusion of the adopted critical scenario at the very end of another, otherwise unrelated, simulator experiment. The main part of this other experiment had subjects drive in a summer environment, evaluating a **lane keeping assistance (LKA)** function, providing warnings or steering wheel torque interventions in the case of lane departures. After completion of this part of the experiment, the simulated truck was moved to the winter highway, and after having received the same instructions and having driven the same initial stretch of road, these subjects also experienced the critical scenario.

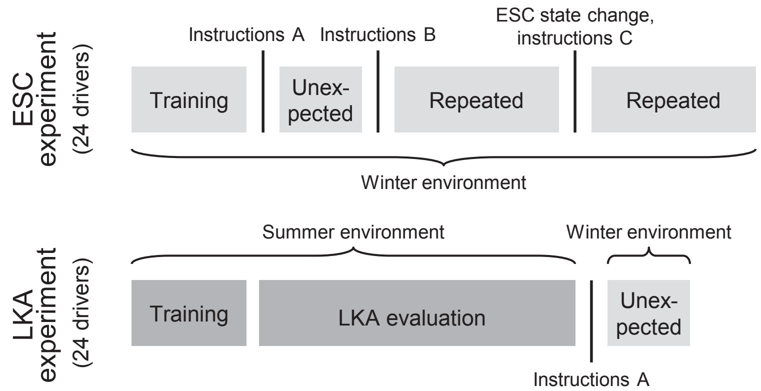

Figure 2.2: *An illustration of the simulator study's experimental procedure. Each block marked "repeated" consisted of a randomized sequence of four overtaking vehicles, eight catch trial scenarios, and six critical scenarios.*

2.3 Scenario tuning

In order to probe the usefulness of ESC, the aim of the unexpected scenario was to get as many of the truck drivers as possible to apply vigorous steering maneuvers (of the type illustrated in Fig. 1.1). In order to determine how to tune the scenario for maximum probability of such steering, a pilot study was carried out, in AB Volvo's fixed base driving simulator in Göteborg.

Also in this pilot study, the critical scenario was appended to the end of another experiment, with twenty-five subjects. Each subject experienced one out of six different versions of the scenario, with a specific combination of *how far ahead* the lead vehicle braked, and *how hard* it braked (T_b and d_b, in Fig. 2.1).

The data thus obtained included too few measurements per scenario version for a quantitative analysis, but a qualitative analysis suggested the following rough model of observed behavior: Drivers applied braking after a reaction time of about 1.5 s (consistent with the brake reaction times, for unexpected events, reported in [30]). Then, about another 1.5 s after brake initiation, drivers applied steering to the left. In practice, this meant that when the scenario was aggressively tuned (e.g. $T_\mathrm{b} = 1.25$ s and $d_\mathrm{b} = 0.45$ g), the drivers often collided without having applied any steering. Conversely, in the least critical scenario versions (e.g. $T_\mathrm{b} = 2.25$ s and $d_\mathrm{b} = 0.35$ g), the drivers had ample margins for a controlled and stable lane change. Intermediate scenario parameterizations, however, elicited large steering maneuvers from a number of drivers, and consequently one of these ($T_\mathrm{b} = 1.5$ s and $d_\mathrm{b} = 0.35$ g) was adopted for the full experiment.

What remained, then, was to set parameters for the repeated and catch

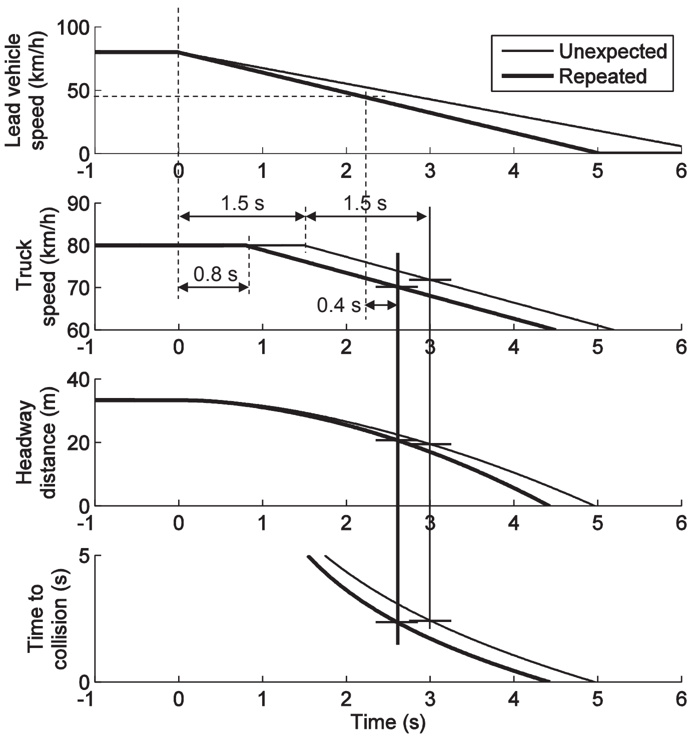

Figure 2.3: *Simple driver-vehicle simulation to choose parameters for the repeated scenario, in order to recreate roughly the same steering avoidance situation as in the unexpected scenario. Brake onset of the lead vehicle occurs at time zero, and the solid vertical lines indicate the times where truck drivers are expected to initiate steering avoidance, in the two scenarios.*

trial scenarios, such that drivers would repeatedly engage in roughly the same type of steering as hoped for from the unexpected scenario. To this end, a simple driver-vehicle model of repeated scenario behavior was used, in which the truck driver starts braking 0.8 s after lead vehicle brake onset (as suggested for expected braking stimuli, in [30]). Then, when the lead vehicle reaches v_3 without beginning to accelerate again, thus revealing to the driver that this is not a catch trial, steering is initiated with a reaction time of 0.4 s (loosely based on [30]). Scenario parameters were then manually tuned to have steering of this model occur at approximately the same truck speed, headway distance, and **time to collision (TTC)** as predicted for the unexpected scenario. As illustrated in Fig. 2.3, this led to the adoption of a slightly higher lead vehicle deceleration ($d_\mathrm{b} = 0.45$ g) for the repeated scenario, and a specific value selected for v_3 (45 km/h) for the catch trials.

Chapter 3

Statistical analysis of driver behavior

In total, the data collection experiment provided 48 measurements of the unexpected collision avoidance scenario, from 48 different drivers and, from 24 of these drivers, an additional 287 measurements of the repeated scenario. Fig. 3.1 shows the totality of recorded vehicle trajectories, providing a qualitative impression of a data set which is constrained in terms of the general type of maneuver being observed, yet diverse in terms of the exact control behavior of drivers. The figure also shows distributions of TTC at steering initiation in the two scenarios, indicating that the preparations outlined in the previous chapter were rather successful: In both scenarios, the most common point of steering initiation was at a TTC between two and three seconds, precisely as predicted by the simple driver-vehicle model illustrated in Fig. 2.3.

Conventional methods for statistical hypothesis testing (t-tests, χ^2-tests, ANOVAs, and non-parametric alternatives when required [23]) were applied to the various collected data variables, to examine the effects of driving experience and ESC on scenario outcome, and to compare driver behavior between the unexpected and repeated scenarios. The technical details are available in Paper I (focusing on driving experience and ESC), and Paper II (focusing on scenario comparison). This chapter provides an overview of the most important results, and is concluded with a brief discussion on the limitations of this type of analysis.

3.1 Results for the unexpected scenario

It is clear from Fig. 3.1 that collision avoidance behavior in the unexpected scenario exhibited considerable variability. Despite all 48 drivers facing ex-

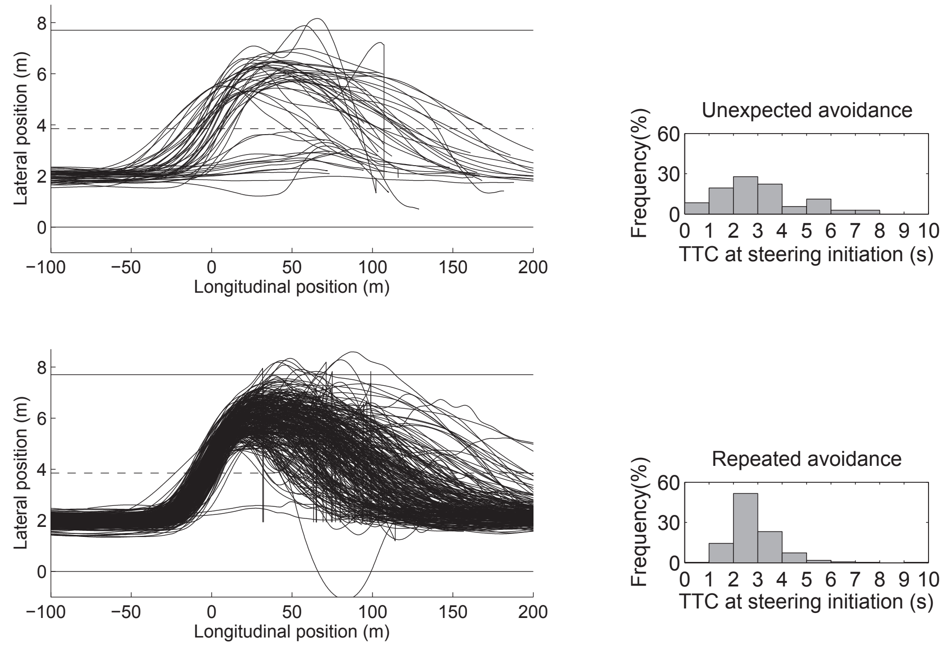

Figure 3.1: *Visualization of the critical maneuvering data collected in the unexpected (top panels) and repeated (bottom panels) scenarios. The panels on the left show the recorded truck trajectories, and the panels on the right show the distributions of time left to collision with the lead vehicle, 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.*

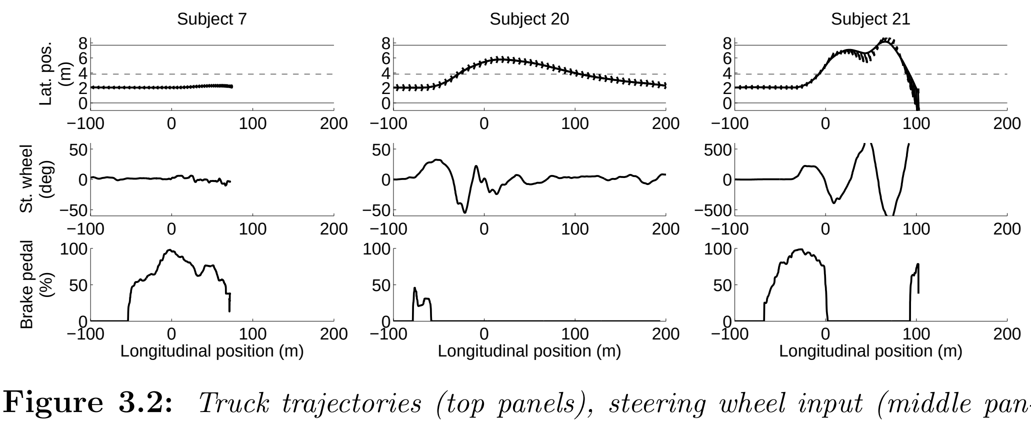

Figure 3.2: *Truck trajectories (top panels), steering wheel input (middle panels, note the variations in scale), and brake pedal input (bottom panels), for three drivers, exemplifying the three typical behaviors observed in the unexpected scenario. The arrows along the trajectories show the forward direction of the truck, and thus indicate skidding (non-zero body slip angle) when pointing away from the trajectory's tangent. Longitudinal position zero corresponds to the point at which the truck's front reached the rear of the lead vehicle.*

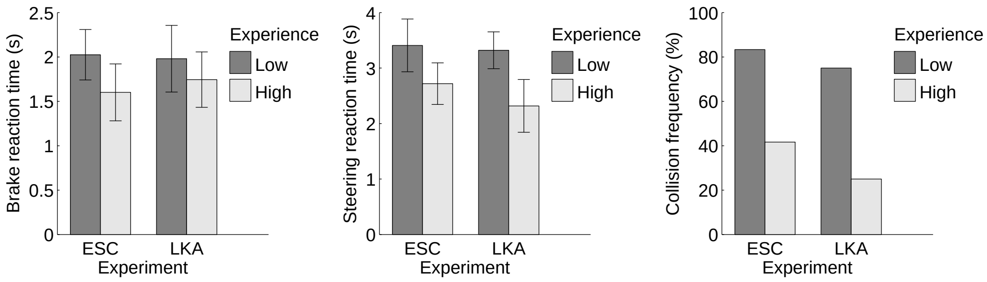

Figure 3.3: *Statistically significant effects of driving experience on reaction times and collisions in the unexpected scenario. Error bars show 95 % confidence intervals.*

actly the same initial situation, the variations in response were, as illustrated in Fig. 3.2, large enough to recreate all three typical behaviors observed in the six scenario variants of the pilot study: braking only and colliding, braking and applying early safe steering, and braking and applying late and more aggressive steering. In total, nine drivers (19 %) applied **ESC-relevant maneuvering**, defined as maneuvering that triggered ESC interventions, or would have triggered interventions, had ESC been active in the truck.

Thus, the effective sample of ESC-relevant behavior in the unexpected scenario was small, and possibly for this reason, no statistically significant effects of ESC on scenario outcome were found. Instead, the main findings in the unexpected scenario were those illustrated in Fig. 3.3, showing that the variations in initial collision avoidance response could to a large extent be attributed to differences in driving experience. As could be expected based on previous literature [12, 78], the experienced drivers exhibited faster brake reactions, and here this difference was present also in the steering reaction times. This, in turn, led to a notable (and statistically significant) difference in collision frequency: 80 % of the novice drivers collided with the lead vehicle, but only 32 % of the experienced drivers. In Paper I, it is proposed that the faster steering reactions of experienced drivers could be attributed to prior exposure, during normal driving, to rear-end conflicts where steering was a suitable maneuver. Such exposure could increase the expectancy for and experience of steering avoidance, and make this type of response a more readily available option in the scenario studied here.

In total, eleven drivers (23 %) did not attempt evasive steering at all, a phenomenon that is well documented from previous experiments and accident reconstructions [2, 49]. A relevant question is whether these drivers would *never* apply steering in this type of situation. Here, a further analysis, illustrated in Fig. 3.4 suggested that this may not be the case. It is known

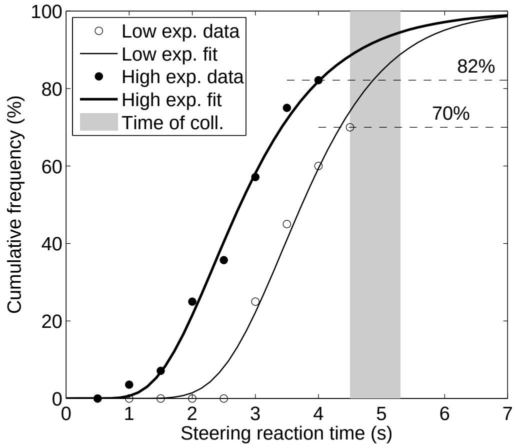

Figure 3.4: *Least-squares fit of log-normal distributions to cumulative steering reaction times, in the unexpected scenario. The shaded region shows the range of times after lead vehicle brake light onset within which all collisions occurred.*

that reaction times are often lognormally distributed [88], but Fig. 3.4 shows that not only the reaction times to steering, but also the fractions of the drivers who attempted steering at all (70 % and 82 %, for novice and experienced drivers, respectively) could be well explained by the same lognormal distributions. In other words, the collected data were compatible with the hypothesis that the drivers who did not steer simply had reaction times that were so long that the collision occurred before steering initiation.

3.2 Results for the repeated scenario

In the unexpected scenario there were thus clear effects of driving experience, but not of ESC. For the repeated scenario, the opposite occurred. As shown in Fig. 3.1, the repeated scenario frequently had drivers initiate steering avoidance from a position close to the lead vehicle (time to collision between two and three seconds), giving a 76 % frequency of ESC-relevant maneuvering[1], and under these circumstances ESC was found to reliably improve truck stability. Fig. 3.5 illustrates the observed statistically significant improvements, in terms of maximum **body slip angle** (i.e. skidding; see Fig. 3.2 for an illustration) and frequency of **full control loss** (departure beyond a road shoulder, or a truck heading perpendicular to the road or worse). There were no indications that these ESC benefits were due to learning effects (see Paper I for details). Interestingly, when analyzing the two

[1]The totality of ESC-relevant steering behaviors is shown on the cover of this thesis.

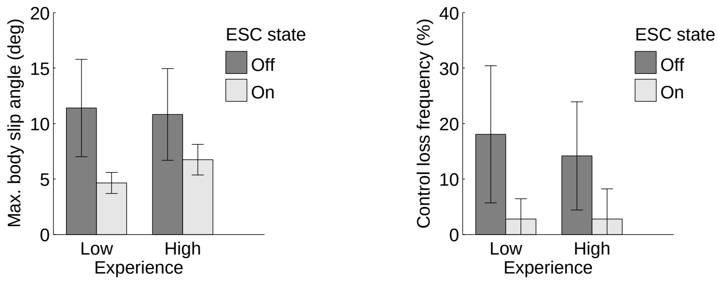

Figure 3.5: *Statistically significant effects of ESC on truck stability in the repeated scenario. Error bars show 95 % confidence intervals, which are here only approximate, due to the data being non-normally distributed. The applied statistical tests, however, did not assume normality (see Paper I for details).*

experience groups separately[2], three out of four effects discernible in Fig. 3.5 remained statistically significant, but not the body slip angle effect for experienced drivers, thus suggesting a smaller benefit of ESC for these drivers. Exactly why this occurred is not clear, but one possibility is that the control strategies of the experienced drivers were less consistent with the built-in assumptions of the ESC system. This could be due to the experienced drivers having some very advanced steering strategies, but just as well to a tendency of overly aggressive countersteering during skidding.

3.3 Comparing behavior between scenarios

Even if the reductions of skidding with ESC were smaller for experienced drivers, ESC still reduced control loss significantly for both experience groups separately. Why were none of these effects observed in the unexpected scenario? If one wishes to prove the value of truck ESC systems, such observations would seem more useful, since the unexpected scenario is, arguably, a better approximation of a near-crash situation in real traffic.

It may be that the lack of statistically significant effects was simply due to the small effective sample of ESC-relevant behavior; an experiment with hundreds of subjects may show significant stability improvements with the system. However, there is another possibility that cannot be immediately rejected: Driver behavior may have differed in some way between the two scenarios, such that the ESC system was less capable of providing its intended assistance in the unexpected scenario. Indeed, some authors have argued that, in unexpected or unusual situations, behavior will shift to qualitatively

[2] Per-group analysis was carried out rather than testing for interactions, since ANOVA assumptions were violated, necessitating the use of non-parametric tests.

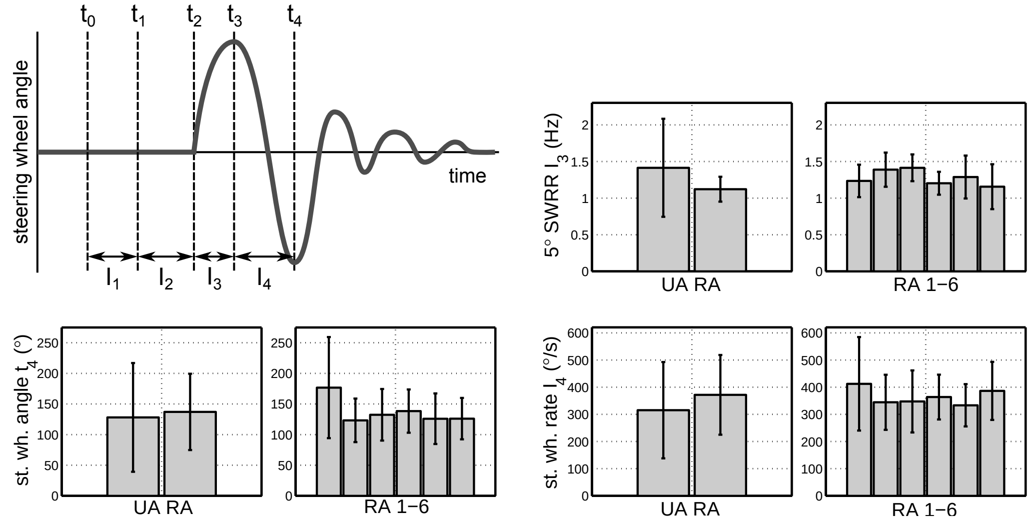

Figure 3.6: *The top left panel shows the division of the observed steering behavior into segments. I_3 is the initial leftward evasive maneuver, and I_4 is the subsequent rightward alignment with the left lane (see Paper II for full details). The other three panels show comparisons between unexpected avoidance (UA) and repeated avoidance (RA), as well as the effect of repetition (RA 1-6), for the following measurements: rate of* $5°$ *steering wheel reversals in I_3 (top right), steering wheel angle at t_4 (bottom left), and maximum steering wheel angle rate in I_4 (bottom right). Error bars show 95 % confidence intervals for the mean.*

different **control modes**, from the planned application of previously learnt procedures, to more opportunistic or even random responses to the unfolding situation [35].

This line of reasoning leads to the idea of comparing behavior between the two scenarios. If it can be shown that unexpected and repeated scenario behavior is similar, it would seem likely that ESC benefits should be observed in a larger study of unexpected maneuvering. Within the context of this thesis, indications of behavioral similarity would also be valuable from another perspective: They would suggest that driver behavior models developed based on the (much larger) set of repeated scenario data can be used to make predictions about unexpected situations. Additional statistical analyses were therefore carried out. In order to ensure a meaningful between-scenario comparison, a selection process (described in detail in Paper II) was applied to the recorded scenarios, leaving a rather small set of only eight drivers with useful data from both scenarios.

Braking behavior in this data set was, as anticipated (see Section 2.3), clearly different between the scenarios, with repeated scenario braking being significantly earlier and harder. However, steering behavior was less affected.

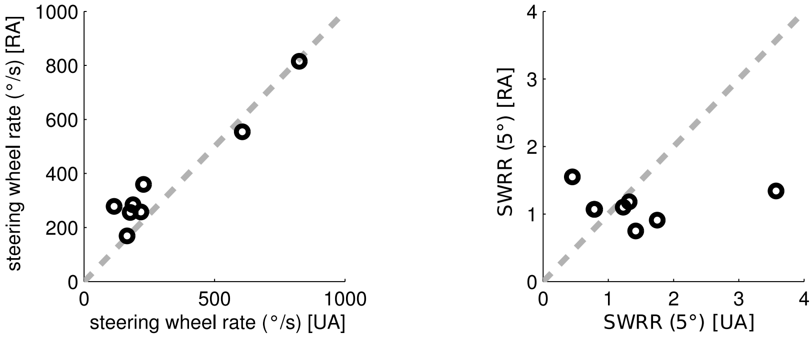

Figure 3.7: *Individual steering behavior, retained between unexpected avoidance (UA) and repeated avoidance (RA), for maximum steering wheel rate in segment I_4 (left panel), but not for steering wheel reversal rate in I_3 (right panel).*

As illustrated schematically in the top left panel of Fig. 3.6, there were some typical features of the truck drivers' steering responses, allowing a structured quantitative description of the first evasion to the left, and the subsequent rightward steering to align with the left lane. In this part of the maneuver, no statistically significant differences were found between the two scenarios, in terms of maximum steering wheel angles, maximum rates of steering wheel movement, or **steering wheel reversal rates** (the frequency of steering wheel corrections [61]). Also, there were no clear indications of learning with repetition[3]. Fig. 3.6 shows a subset of the tests carried out.

Another relevant question is whether individual differences in steering behavior were preserved in the shift from unexpected to repeated steering. As exemplified in the left panel of Fig. 3.7, this was the case for maximum steering wheel angles and rates: Most notably, the two drivers who applied aggressive steering wheel movements in the unexpected scenario, did so to similar extents also in the repeated scenario. However, as seen in the right panel of the same figure, steering wheel reversal rates in the repeated scenario were lower for most drivers. A decrease in reversal rate can be interpreted as more smooth steering, providing a possible link to the concept of control modes, and to the idea of experience and expectancy leading to control behavior which is more open-loop and smooth in nature [20, 35].

[3]Statistical hypothesis testing of learning effects was not performed, but correlation with repetition was $|r| < 0.2$ for all examined variables.

3.4 Limitations of the statistical analysis

The analyses presented above provide partial answers to the research questions formulated in Chapter 1: ESC has been shown to enhance truck stability in a repeated rear-end scenario, for novice and experienced drivers, but slightly less for the latter group. Furthermore, there seems to be more similarities than differences between behavior in the repeated and unexpected scenarios, suggesting that it may be possible to generalize between the two experimental settings. However, some clear limitations remain.

First, the division of the subjects into two groups, based on driving experience, is rather crude. Even if ESC provides support to the average novice or experienced driver, this does not show that ESC is equally helpful for every single individual. Indeed, for seven (29 %) of the twenty-four drivers in the ESC experiment, average skidding *increased* slightly with ESC. Here, however, one runs into a problem of too little data. Six measurements with ESC and six without is not enough to show a statistically significant effect of ESC even for the driver where the difference between ESC off and ESC on was the greatest. Currently, data are too scarce to clarify statistically whether the observed between-driver differences in ESC performance were due to any interesting differences in driver control strategies, or whether they were just random occurrences caused by the natural variability inherent in human behavior. For example, the drivers concerned may just have happened to initiate steering slightly later, on average, in the repetitions with ESC, making the stabilization task faced in these repetitions more difficult. Given such limitations in repeatability, it may be virtually impossible to study the benefit of ESC for individual drivers using statistical analysis alone.

Second, one thing that statistical hypothesis tests can definitely not be used for, is to demonstrate the *absence* of an effect[4]. Thus, the fact that no statistically significant behavioral differences were found between the unexpected and repeated scenarios does not prove that there were no such differences. The value of the comparative analyses is further constrained by the necessary limitations in the number of included drivers, and the exclusion of the later, stabilization-oriented phases of steering, where behavior was more diverse and less easy to quantify on a high level, such as in Fig. 3.6.

The remainder of this thesis will be devoted to showing how driver behavior models can (a) be used to provide more positive and complete evidence of behavioral similarity, and (b) allow a more detailed study of individual driver behavior in relation to an active safety system such as ESC.

[4]In the terminology of statistical analysis: One can fail to reject the null hypothesis, but one cannot prove it.

Chapter 4

Analysis of driver behavior using models

In science, the term **model** generally refers to "a simplified description of a system or process" [1]. In this sense, science often consists of constructing and testing models, describing some specific systems or processes of interest, either in terms of their internal functioning or their observable outcomes (or both). The aim of driver behavior modeling is to provide such descriptions of the systems and processes relevant to human vehicle driving. The conceptual framework of Ljung Aust and Engström outlined in Chapter 1 clearly shares this aim, and could therefore be referred to as a **conceptual driver behavior model**. Statistical descriptions of driver behavior phenomena, such as those provided in Chapter 3, could be termed **statistical driver behavior models**, and descriptions at a level of detail sufficient for computer simulation will here be referred to as **simulation-ready driver behavior models**[1].

The first section of this chapter provides an overview of currently available simulation-ready models, summarizing the literature review in Paper III, but with an emphasis on models of steering. The subsequent sections present previously unpublished work, demonstrating the ability of an existing driver model to reproduce the steering behavior observed in the ESC experiment presented in the previous chapters. A final section then provides mathematical derivations relating this model to vehicle dynamics.

[1]Developers of active safety systems sometimes use the term driver model for referring to a real-time estimate of a driver's current state or intentions [41]. While such an estimate is, in a sense, also a "description of systems or processes" related to the driver, this use of the term is not adopted here.

4.1 Existing models of near-accident driver behavior

At the outset of this research project, it was clear that a wealth of driver behavior models was already in existence. However, it was less clear how many of these existing models had been tested in simulation of near-accident situations, and, even more importantly, how many of them had been verified to reproduce near-accident behavior of human drivers. Therefore, a systematic review of recent literature (publication year 2000 or later) was carried out. Over 5000 database search hits were considered, and after a structured filtering process, in which the scope was limited to models of behavior in *near-collision* situations, around 100 relevant models remained. These models, describing driver braking or steering control behavior (sometimes both) in reaction to a collision threat, were summarized and discussed in Paper III.

A rather surprising finding from the review was that, despite the large number of existing models, actual simulation-based comparisons of models have been very rare in the literature. Therefore, in Paper III, such comparisons were carried out between some of the reviewed models, in selected traffic scenarios. These comparisons indicated that models may sometimes be more similar to each other than what the model equations could be taken to suggest. The most striking example concerns the *timing* of deceleration initiation by a driver who is catching up with a slower or stationary lead vehicle: The left panel of Fig. 4.1 shows how three models, mathematically very different from each other, predict the same general pattern of how deceleration timing is affected by vehicle speed. As a further example, the right panel of the same figure suggests that, in a simulated single lane change scenario, all tested models of steering would have been equally successful at avoiding collision with an obstacle at 40 m longitudinal position.

However, on a more detailed level, the steering behaviors illustrated in the right panel of Fig. 4.1 clearly differ considerably from each other. All of the models in the figure apply concepts from **control theory** [40] in order to have the vehicle follow a predefined **desired path**, but they do so in different ways. The Guo *et al.* [32] model uses a simple **internal vehicle model** to calculate the steering that will remove the deviation between predicted and desired paths at a single **preview point** ahead of the vehicle. The MacAdam [57] model instead takes an **optimal control** approach, and minimizes the predicted *average* path deviation in an entire **preview interval**. The Sharp *et al.* [79] and Chatzikomis and Spentzas [10] models do not use internal vehicle models, but instead measure the deviation between the current forward direction of the vehicle and the desired path, and calculate

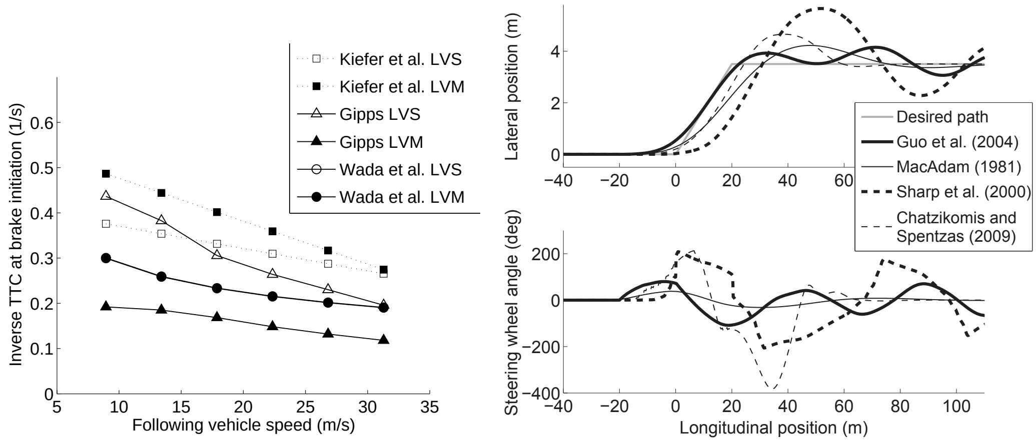

Figure 4.1: ***Left:*** *Timing of deceleration initiation as a function of speed, as predicted by three models of braking in scenarios with a stationary or slower moving lead vehicle (LVS and LVM, respectively).* ***Right:*** *Vehicle trajectories and steering wheel angles predicted by four models of steering, in a single lane change scenario.*

their steering wheel angles as weighted sums of errors in lateral position or heading, at multiple preview points along this forward direction.

In terms of model validation, only very few of the braking models, and none of the steering models, were found to have been compared to actual human behavior in unexpected critical situations. Some of the steering models have been tuned to reproduce human steering in test track maneuvers such as double lane changes but, as discussed in Chapter 1, it is not clear to what extent such behavior is a valid approximation of real near-accident behavior.

4.2 The Salvucci and Gray model of steering

A model of steering that has not previously been tested in simulation of near-collision situations, and was therefore not reviewed in Paper III, is that of Salvucci and Gray [77]. This model is mathematically similar to the above-mentioned models by Sharp *et al.* [79] and Chatzikomis and Spentzas [10], in that it calculates its steering command as a linear combination of a number of error terms. As illustrated in Fig. 4.2, the model uses the visual angles θ_{n} and θ_{f} from the vehicle's forward direction to one **near point** and one **far point**, and applies a rate of change $\dot{\delta}$ of the steering wheel angle, aiming to reduce the near point angle to zero and to keep the angles to both the near and the far point constant over time:

$$\dot{\delta} = k_{\mathrm{nI}}\theta_{\mathrm{n}} + k_{\mathrm{nP}}\dot{\theta}_{\mathrm{n}} + k_{\mathrm{f}}\dot{\theta}_{\mathrm{f}} \tag{4.1}$$

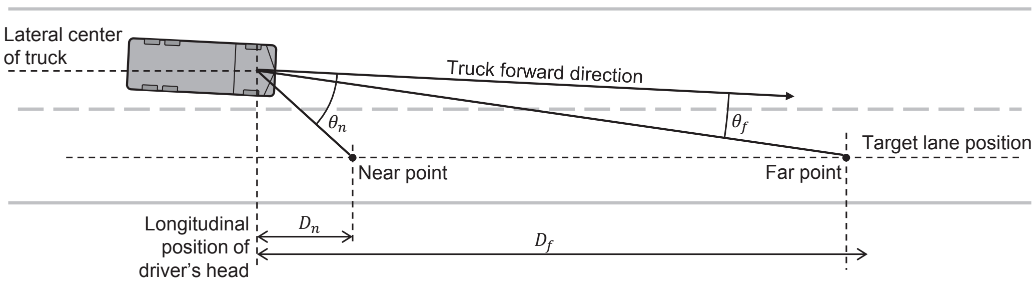

Figure 4.2: *An illustration of the input quantitites used by the two-point visual control model of steering, proposed by Salvucci and Gray [77]. Instead of defining the sight point angles based on the lateral center of the truck, one could equally well use the driver's lateral head position, but then the target lane position would also have to be a target position for the driver's head, and not for the truck. The model behavior is the same in both cases.*

Compared to the other models mentioned above, this model is to a greater extent based on prior knowledge regarding the types of visual information that drivers use when steering, and how: There is empirical support both for the choice of having visual input separated into near and far information [48], and the choice of predicting the rate of change of the steering wheel angle [96], rather than predicting the steering wheel angle directly.

4.3 Fitting the model to repeated scenario behavior

Is the Salvucci and Gray model capable of exhibiting the type of steering behavior observed in the ESC experiment described in Chapter 2? In order to answer this question, optimization of the model's parameters was carried out, using a **genetic algorithm (GA)** [34,93], combined with least-squares curve fitting. The aim of this parameter optimization was to have the model's steering match the human repeated-scenario steering as closely as possible in the **stabilization phase**, defined here to begin at the moment when the truck driver initiated the rightward steering movement to align with the left lane (roughly corresponding to t_3 in Fig. 3.6), and to end at whichever occurred first of (a) the truck traveling 250 m after reaching the lead vehicle (b) full control loss, or (c) truck speed falling below 5 km/h.

The optimized parameters were those mentioned in the previous section (the distances D_n and D_f to the near and far points, and the linear control gains k_nI, k_nP, and k_f), as well as a neuromuscular delay time parameter

T_R, from visual input to control output[2]. Additionally, two parameters were included allowing for differences in the target lateral position Y in the left lane (some drivers seemed to consistently steer further to the left than others) and the distance X, after passing the lead vehicle, at which the target lateral position was shifted to the middle of the right lane to initiate a lane change.

Optimization was carried out per driver, using the approach of **hold-out validation**, whereby the repeated-scenario data for each driver were randomly divided into one **training set** and one **validation set**, with six repetitions of the scenario in each. In each driver-specific optimization, an initial set of 50 parameter settings (in GA terminology, a **population** of 50 **individuals**) were selected at random, including values for all parameters except the three linear control gains. For each of the 50 GA individuals, the inputs to the model (θ_n, $\dot{\theta}_n$, and $\dot{\theta}_f$) were calculated, and linear least-squares fitting was applied to find optimal values of k_{nI}, k_{nP}, and k_f for the training set. Next, the success of this model fitting was calculated for each individual, in terms of the quantity R^2, signifying the amount of variance in the data explained by the model [23]. Values of R^2 were computed separately for the training and validation set. The values computed for the training set were used as the **fitness measure** (the quantity to be maximized) for the GA. Using **tournament selection**, individuals with high training fitness (high values of R^2 on the training set) were selected for inclusion in the next 50-individual **generation**, and **crossover** between pairs of individuals (yielding an offspring individual with some of the parameter values from one of the parents, and the rest from the other), as well as small random **mutations** were used to introduce variations. Optimization by this approach can, depending on the flexibility of the model being fitted, lead to arbitrarily close fits of the training set. To prevent **overfitting**, the final parameter setting was therefore selected by finding the individual with the highest observed fitness on the *validation set*. For full details on the methods mentioned in this paragraph, see [93].

Preliminary optimization tests indicated that the exact values of D_n and D_f did not make a major difference for the model's ability to fit the data. Therefore, to reduce the number of free parameters, D_n and D_f were fixed at the median values of those obtained in tests where these parameters were not fixed: 1.5 m and 82.5 m, respectively. Final optimization of the resulting six-parameter model (k_{nI}, k_{nP}, k_f, T_R, X, Y) resulted in an average $R^2 = 0.69$ for the validation set ($R^2 = 0.77$ for the training set). Fig. 4.3 provides examples

[2] Salvucci and Gray [77] only indirectly discuss such a delay, and it is not clear whether one was included in their model. However, the optimization here allowed $T_R = 0$, i.e. no delay, to occur.

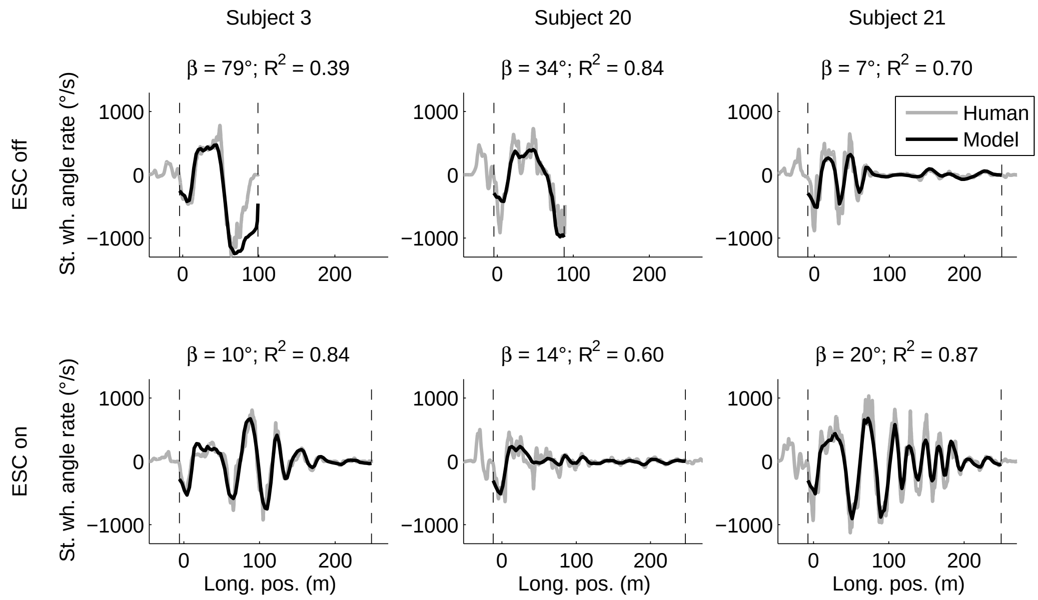

Figure 4.3: *Comparison of stabilization steering behavior between human drivers and the Salvucci and Gray model, in six example instances of the repeated scenario. The specific scenario instances shown (with and without ESC) are selected to give an impression of the average performance of the model. The dashed vertical lines indicate the beginning and end of the stabilization phase, and β denotes maximum body slip angle.*

of the match between human and model steering, suggesting that the model was able to reproduce the overall steering strategies, and that the two main sources of variability that the model was not able to capture were (a) high-frequency variations in the rate of steering wheel angle movement, and (b) situations where drivers reduced steering wheel speed in the second or two before full control loss (top left panel of Fig. 4.3), something which could be interpreted as resignation in the face of obvious stabilization failure [44].

4.4 Testing the model on unexpected scenario behavior

One question left open by the statistical analyses of Chapter 3 was to what extent driver stabilization behavior was similar between the repeated and unexpected scenarios. Here, the driver model was used to investigate this matter: For each of the 16 drivers who applied evasive steering in the unexpected scenario of the ESC experiment, the model's prediction of this steering was

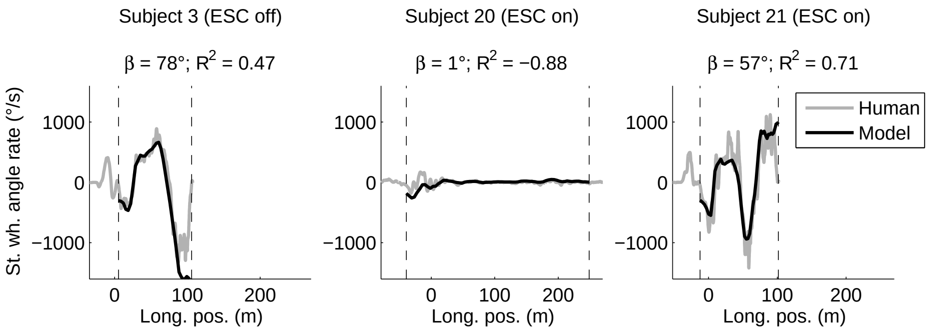

Figure 4.4: *Comparison of stabilization steering behavior between human drivers and the Salvucci and Gray model, in the unexpected scenarios experienced by the same drivers as visualized in Fig. 4.3. Note the moderate maneuvering in the middle panel, due to the early initiation of steering avoidance (cf. Fig. 3.2). The dashed vertical lines indicate the beginning and end of the stabilization phase, and β denotes maximum body slip angle.*

calculated, using the model parameter values optimized for the same driver's repeated scenario behavior. Fig. 4.4 provides examples of the obtained model outputs.

When taking all 16 drivers into account, the average R^2 for the unexpected scenario was 0.34. This reduced average model performance seemed to be due mainly to scenario instances such as that shown in the middle panel of Fig. 4.4, where steering was moderate and almost no skidding occurred. However, when including in the analysis only drivers reaching some minimum body slip angle β in the unexpected scenario, the average model fit increased, to $R^2 = 0.44$ for $\beta > 1°$ (13 drivers), to $R^2 = 0.59$ for $\beta > 2°$ (6 drivers), and to $R^2 = 0.63$ for $\beta > 3°$ (4 drivers).

These R^2 values, together with the qualitative impression of the fit in the leftmost and rightmost panels of Fig. 4.4 (note the possible signs of steering resignation in the leftmost panel) can be taken to suggest that when skidding occurred, drivers handled this in the same way in the unexpected and repeated scenarios.

4.5 Relating the model to vehicle dynamics

While the Salvucci and Gray model has a relatively solid foundation in psychology, compared to the models reviewed in Section 4.2, it may seem less impressive from an applied engineering perspective. Most notably, in contrast with the Guo *et al.* [32] and MacAdam [57] models, it does not include an internal vehicle model. It is known that drivers adapt to the dynamics of

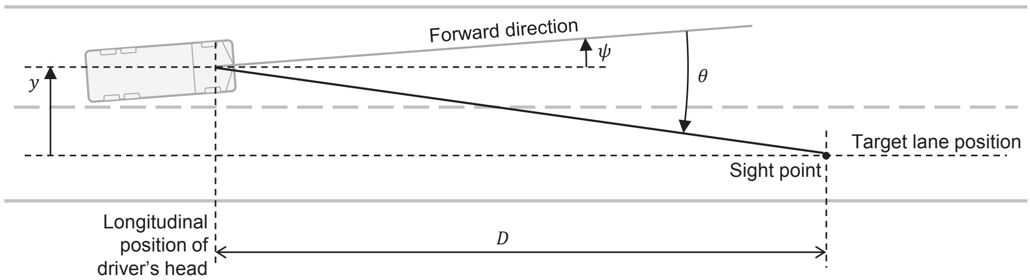

Figure 4.5: *Illustration of the mathematical quantities used in Section 4.5.*

their vehicle, such that externally measured vehicle behavior remains roughly constant across vehicles for a given driver [58], and an important benefit of internal vehicle models is that they allow modelers a cost-efficient means of accounting for this phenomenon: Instead of collecting new human behavior data for every vehicle, something which seems especially undesirable in a truck context, where the variety of vehicle combinations is so large, one can simply measure the dynamic properties of a given new vehicle and feed these to an existing driver model. Here, a first sketch will be provided of how the Salvucci and Gray model can possibly be extended in this direction.

Consider a situation where a vehicle is initially (time $t = 0$) at the driver's target lane position $y = 0$, with a heading $\psi = 0$ along a straight road, but with a non-zero steering wheel angle δ_{err}. The resulting yaw rate of the vehicle can be approximated by the steady-state response of a **linear bicycle model** [39]:

$$\dot{\psi} = \frac{Gv_x\delta_{err}}{L(1 + Kv_x^2)} \tag{4.2}$$

Conversely, the steering wheel adjustment that the driver should apply in order to correct the vehicle's rotary motion can be written:

$$\Delta\delta = -\delta_{err} = -\frac{L(1 + Kv_x^2)}{Gv_x}\dot{\psi} \tag{4.3}$$

In these expressions, v_x is the longitudinal speed, G is the **steering gear ratio** (how much the front wheels rotate for a given rotation of the steering wheel), L the **wheel base** (for a two-axle vehicle, the distance between front and rear axle; see [97] for the equivalent wheel base for a three-axle truck such as in the data collection experiment in Paper I), and K the **understeer gradient** (quantifying how much the driver needs to increase the steering wheel angle, after a speed increase, to maintain the same turning radius). The non-zero yaw rate in Eq. (4.2) causes the vehicle's lateral speed, relative to the target lane position, to increase over time, and for small t the movement can be written as $\dot{y} = \dot{\psi}v_xt$.

What does this do to the movement of a sight point, such as the near or far points of the Salvucci and Gray model? The angle to a sight point at distance D ahead of the vehicle can be written $\theta = -\psi - \arctan(y/D)$, and differentiation yields:

$$\dot{\theta} = -\dot{\psi} - \frac{D\dot{y}}{D^2 + y^2} = -\dot{\psi} - \frac{D\dot{\psi}v_x t}{D^2 + y^2} = -\dot{\psi}\left(1 + \frac{Dv_x t}{D^2 + y^2}\right) \tag{4.4}$$

Now, for the far point of the Salvucci and Gray model, where $D \gg y$, this reduces to $\dot{\theta} \approx -\dot{\psi}\,(1 + v_x t/D)$, and initially, while t is small enough for $v_x t \ll D$, the movement of the far point can thus be written simply as:

$$\dot{\theta}_\mathrm{f} \approx -\dot{\psi} \tag{4.5}$$

Insertion of this equation into Eq. (4.3) gives a new expression for the required steering wheel correction:

$$\Delta\delta = \frac{L(1 + Kv_x^2)}{Gv_x}\dot{\theta}_\mathrm{f} \tag{4.6}$$

If a driver wishes to achieve this correction in a steering wheel movement of duration Δt, his or her average rate of steering wheel rotation should be:

$$\dot{\delta} = \frac{\Delta\delta}{\Delta t} = \frac{L(1 + Kv_x^2)}{Gv_x\Delta t}\dot{\theta}_\mathrm{f} \tag{4.7}$$

This is now recognizable as the far point control law of the Salvucci and Gray model, with $k_\mathrm{f} = L(1 + Kv_x^2)/Gv_x\Delta t$.

The above analysis is basic[3], but it nevertheless shows that the far point control of the Salvucci and Gray model can be reasonable also from a vehicle dynamics perspective. Not the least, Eq. (4.7) provides a prediction of how driver adaptation to a new vehicle may be reflected in the k_f parameter, something which could be tested empirically.

Another possible prediction that could be made based on Eq. (4.7) concerns the $(1+Kv_x^2)/v_x$ factor, suggesting that it would also make sense, from a vehicle dynamics perspective, for k_f to vary with vehicle speed. However, there is of course no guarantee that drivers are this sensible in reality, and it could be argued that it seems easier to learn a control behavior which is speed-independent[4]. Again, this a matter for empirical testing.

[3]Perhaps especially in that it does not let the driver correct for his or her own neuromuscular delays.

[4]At least at high speeds, where $(1 + Kv_x^2)/v_x$ will, for typical values of K [39,97], vary considerably less than at low speeds.

A final point worth noting is that, as a model parameter, Δt has a much clearer interpretation than k_{f}, another benefit of a formulation such as in Eq. (4.7). Furthermore, it does not seem unreasonable that the same Δt could be reused in a similar reformulation of near point control, thus possibly allowing the replacement of also k_{nI} and k_{nP} with expressions based on Δt and vehicle properties.

However, there may be room for improvement of the Salvucci and Gray model's near point control also in other respects, and this will be one of the topics of discussion in the next chapter.

Chapter 5

Discussion

This chapter begins with a discussion on the topic of how to model driver steering behavior, with emphasis on the previously unpublished work presented in Chapter 4. Next, the most important empirical results of the thesis are summarized, with one section on driver behavior in unexpected critical situations, and one on the impact of ESC in such situations. Two final sections address issues related to driver behavior models in general: the different ways in which they can be put to use, and how to know when their performance is acceptable for the intended purposes.

5.1 Modeling steering behavior

The results reported in Chapter 4 show that the Salvucci and Gray [77] model was able to account for a considerable fraction of the variance in the steering behavior of human drivers, in both repeated and unexpected stabilization maneuvering. Specifically, the model seemed capable of capturing the overall strategy of steering control during yaw instability, and the variance left unexplained appears mainly to have consisted of high-frequency variations in steering wheel rate, possibly attributable to neuromuscular **motor noise** [26]. In any case, these high-frequency variations are to a large extent averaged out in the resulting steering wheel angle signal, and may thus be less important in the context of vehicle stability and ESC evaluation.

In the literature, steering models have frequently been parameter-fitted to reproduce driver behavior as measured on cone tracks and the like, but to the author's knowledge, this is the first time that a steering model has been shown to reproduce human behavior in an unexpected critical situation. Furthermore, considering also the previous work based on test track data, this may be the first time that a model has been fitted to behavior during severe yaw instability.

In the literature review presented in Paper III, it was noted that there seem to be two main perspectives on driver behavior modeling: Some researchers take an applied, engineering approach, and are mainly interested in models as cost-efficient, multi-purpose *tools*, which should provide adequate approximations of behavior in as many different traffic scenarios as possible. Other researchers are more interested in elucidating the *psychological mechanisms* underlying observed behavior, and the Salvucci and Gray model comes from this type of research context. Neither perspective is inherently superior to the other, but this author would argue that there are at least two good reasons, also from an applied perspective, to aim for models which are psychologically plausible: (a) A model based on appropriate underlying mechanisms may generalize better beyond the specific data set to which it is fitted. (b) As exemplified by the Salvucci and Gray model, insights on what perceptual information humans are using in their control behavior may allow formulation of rather simple yet effective control laws[1], considerably less complex than many of the models reviewed in Paper III.

Thus, the two perspectives are by no means incompatible by definition, and the mathematical derivations in Section 4.5 show how they could even be completely aligned for the far point control of the Salvucci and Gray model. However, conflicts do exist. For example, an *internal vehicle model* provides a simulation engineer with an immediate prediction of how a driver could be expected to behave in a new vehicle. However, a driver with such an internal model of vehicle dynamics should arguably be able to successfully perform brief maneuvers, such as lane changes, even without feedback from the surroundings, but experiments have shown that humans are not capable of such feats [11]. Furthermore, a *desired path* provides a simulation engineer with a very flexible means of defining an arbitrary traffic scenario, but recent neurobiological models of sensorimotor control (so far of much simpler tasks than driving) seem to move away from this type of construct, instead placing emphasis on more discretely defined **goal states**, and how humans are able to reach these states with sufficient precision and minimal effort [26, 86].

This latter idea, of good enough task performance with minimal effort, was referred to as *satisficing* in Chapter 1, and it may be noted that the Salvucci and Gray model does *not* include such a concept. This seems like a limitation, especially when it concerns the $k_{\mathrm{nI}}\theta$ control term, which suggests

[1]In the words of Neisser: "If we do not have a good account of the information that perceivers are actually using, our hypothetical models of their 'information processing' are almost sure to be wrong. If we do have an account, however, such models may turn out to be almost unnecessary." [68] (quoted in [25])

that drivers will react with steering as soon as the vehicle is not exactly at the target lane position. Here, other models reviewed in Paper III may be capable of more credible behavior [9, 28, 102]. This limitation of the Salvucci and Gray model could be an important factor in explaining the inability of the model, when fitted to scenarios with skidding, to reproduce well the behavior in less critical steering (such as in the middle panel of Fig. 4.4); as discussed in Chapter 1, satisficing should be expected to be more pronounced farther away from the safety zone boundary.

5.2 Driver behavior in critical situations

If the inability of the Salvucci and Gray model to fit both severe and moderate steering with the same parameterization could be remedied, for example by inclusion of satisificing concepts, this would be an important finding, since it would provide an indication that drivers' control strategies may stay the same in the transition from normal driving to critical maneuvering. The analyses presented here do not allow such a conclusion, but they do accommodate the idea of behavioral constancy in another, partly related transition, namely from unexpected critical maneuvering to expected critical maneuvering. Considering the statistical tests in Paper II and the model-based analyses in Chapter 4, the only clear indication of a change in control behavior between the unexpected and the repeated scenario is the reduction in steering wheel reversal rate during the initial leftward evasive maneuver (Fig. 3.7). This suggests that if a change in control mode occurred, it did not affect the overall control strategies, only the drivers' performance in effectuating these strategies, for example in the form of steering becoming more open-loop in nature.

This is an important result in general, since it implies that premeditated severe steering behavior may be a valid approximation of unexpected severe steering. In this sense, the results presented here actually provide some support for the use of test tracks as an evaluation tool. Typical cone tracks may still constrain driver decision-making more than many naturalistic situations, and avoiding collision with a cone may still be emotionally different from avoiding collision with another road user. However, barring these limitations, test track steering behavior (at least that of normal drivers, as opposed to professional test drivers) may be similar to steering in unexpected critical situations in real traffic. A method of addressing the mentioned limitations of cone tracks could be to adopt repeated avoidance paradigms for the driving simulator, such as the paradigm introduced in Paper I, developed according to the process outlined in Chapter 2 of this thesis[2].

The statistical analyses in Paper I also confirmed some previous results regarding decreases in reaction time with increases in expectancy or driving experience [12, 30, 78]. However, the interpretation of non-steering reactions as slow steering reactions (Fig. 3.4) may be a novel contribution.

An interesting question is how the concept of reaction times, which seems valid close to the safety zone boundary, can be reconciled with the concept of satisficing, as assumed to occur in the comfort zone. It may be that some existing neurobiological models, describing response selection as noisy integration of sensory evidence over time [71, 80], could account for the lack of immediate reactions, typical for satisficing behavior, as very slow (or, equivalently, improbable) reactions to low-intensity stimuli.

5.3 Benefits of ESC in unexpected critical situations

Within the context of this thesis, the indications that drivers' stabilization control strategies were preserved between unexpected and repeated scenarios also have a more specific implication, in allowing a more complete answer to research question (A) from Chapter 1: *Does heavy truck ESC provide a safety benefit to normal drivers in realistic near-crash scenarios?*

In Paper I (see also Chapter 3 above), the possibility could not be excluded of a qualitative change in behavior between repeated and unexpected critical maneuvering. For this reason, the existence of stability improvements with ESC could only be proven for the repeated scenario. However, given the analyses in Paper II and Chapter 4, it now seems very likely that these benefits should be present also during unexpected critical maneuvering. Since there have been no naturalistic evaluations of heavy truck ESC[3] (to the author's knowledge), and previous demonstrations of ESC benefits for heavy trucks have been based on test track tests or equivalent computer simulations [47, 84, 98], this thesis may provide the first evidence of benefits of heavy truck ESC for normal drivers in unexpected yaw instability.

[2] Interestingly, with regards to the emotional aspects of collision avoidance, the video logs from the data collection experiment show some rather strong emotional responses to the unexpected scenario, despite the lead vehicle being entirely fictitious.

[3] Current market penetration rates may still be too low for accident statistics studies [98].

5.4 Applications for driver behavior models

The discussion above highlights one way in which simulation-ready driver models can be useful, namely in the comparison of behavior between slightly different contexts. Consider, for example, the two measurements for Subject 21 visualized in Fig. 4.3. It would have been difficult to compare these two measurements in any meaningful way using metrics of the type adopted in Paper II (see also Section 3.3 above). However, the fit of the driver behavior model also seen in the figure rather convincingly demonstrates that the same overall control strategy was at play in both cases.

Another important feature of models, in general, is their ability to provide predictions about novel situations, either as **interpolation** between previously observed situations, or as **extrapolation** beyond them. Exactly how well a given model will generalize to a new situation is of course difficult to know beforehand, but this thesis provides one specific illustration of successful prediction of previously unobserved behavior: The simple driver-vehicle model described in Paper I and Section 2.3 above was able to predict average steering initiation timing in the two simulated scenarios, something that was crucial for successful scenario tuning. A less successful generalization was seen in Chapter 4, where it was found that the Salvucci and Gray model parameterized for severe yaw instabilities did not extrapolate well to less severe steering.

However, it seems to be the case that the Salvucci and Gray model, parameterized as in Chapter 4, could provide useful interpolations, as in predictions of behavior in severe yaw instabilities, similar to those observed in the experiment. Thus, given another main strength of model-based testing, the virtually unlimited *repeatability*, it would now appear possible to revisit also research question (B) from Chapter 1: *Is ESC more useful for some drivers than for others?* As noted in Chapter 3, the collected data set of human behavior was too small, despite the repeated scenario paradigm, for a conventional statistical analysis at the individual level. An even more concrete illustration of this limitation is provided by again considering the two measurements from Subject 21 in Fig. 4.3, and noting that the period of oscillatory instability lasted longer with the ESC system than without it. Was this finding due to some undesired effect of the system, or to other factors, such as a higher initial speed or a later collision avoidance?

Fig. 5.1 provides a preliminary idea of how driver models can be used to answer this type of question. Here, the model parameterization obtained for Subject 21 has been used in a **closed-loop simulation**, with the same truck model as in the data collection experiment, and it is clear that also in this simulation there are considerable oscillations with the ESC system turned

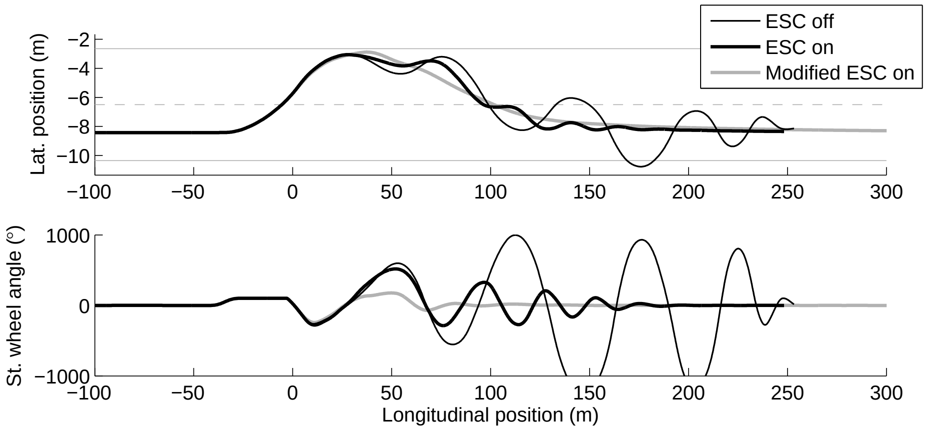

Figure 5.1: *Example results of closed-loop simulation with the Salvucci and Gray steering model, with parameters optimized using the behavior data from Subject 21 of the data collection experiment. This figure serves mainly to illustrate the potential of simulation-based evaluation methods; full details are not provided here.*

on. However, since it is possible to simulate *exactly* the same initial situation both with and without ESC, it can be shown that these oscillations become even larger without the system, giving a clear indication of the benefit of the system in this specific situation. With this type of approach, it is possible to study in detail how beneficial ESC is for different modeled drivers, something that will be explored in forthcoming publications.

Finally, an increased knowledge about driver behavior in the form of a quantitative model can also guide system development in itself. Here, the good fit of the Salvucci and Gray model can be taken to suggest that even if today's ESC systems provide reliable improvements of vehicle stability, there is still room for further improvement. Current ESC systems typically assume that drivers make use of an internal vehicle model to translate a desired vehicle motion into steering wheel angles [84, 91]. The Salvucci and Gray model, on the other hand, suggests that drivers do not at all care about exact steering wheel angles, but instead keep rotating the steering wheel as long as the vehicle is not moving as desired. Such behavior can in some circumstances clearly lead to overcompensation and oscillatory instability, as seen in Figs. 4.3 and 5.1. An ESC system incorporating this type of model could potentially achieve a better understanding of the driver's intentions, and could actively damp any overcompensatory driver behavior. Simulation results for such a modified ESC system show promise (see Fig. 5.1), but further investigation is needed in order to prove this concept in real driving. More details are available in the corresponding patent application [60].

5.5 Validating driver behavior models

An interesting question is whether the results discussed above constitute a **validation** of the Salvucci and Gray model. As mentioned in Paper III, this is another area where there may be a distinction between an applied perspective and a more psychology-oriented one. From the point of view of the simulation engineer, the good model fits obtained here, on the training and validation sets, and on the previously unseen set of unexpected maneuvering[4], can constitute a sufficient validation in the sense that the obtained model parameterizations seem to provide a useful approximation of driver behavior in situations with severe yaw instability. Other models could provide even better fits, in wider ranges of scenarios, and if it can be shown, as here, that such a better fit does not seem to be due to overfitting, then these models should be the tools of choice for the application at hand.

However, the Salvucci and Gray model can also be understood as making some claims about underlying mechanisms, and it is important to note that the model fits reported in Chapter 4 do not prove, for example, that human drivers really use something like near and far points in their steering control. Had the Salvucci and Gray model been utterly unable to fit the data, one could have rejected the model, but anything else may simply be a result of the model being flexible enough to achieve the fit [76]. In this sense, descriptive science cannot prove models to be fundamentally true, only maintain a list of models that have not yet been disproven[5], and the concept of *validation* is thus mainly relevant from an applied perspective.

If one wishes to study underlying assumptions, such as those of the Salvucci and Gray model, in more detail, two important approaches would be to: (a) compare the data-fitting abilities of the model to that of other models, based on other underlying assumptions, while at the same time controlling for the relative flexibilities of the various models [23, 67]; (b) use the model to make specific, and preferably somewhat unexpected, predictions, and collect data which could refute these predictions [76].

As discussed in Paper III, regardless of perspective, testing and comparison of simulation-ready models has so far been very rare within the field of driver behavior, and surprisingly few modelers have even used such simple concepts as R^2 to quantify model performance. Thus, this appears to be an area where much valuable progress could be made with relatively little effort.

[4] In this sense, the unexpected scenario data can be regarded as a type of **test set** [93].

[5] This argument is analogous to that made in Section 3.4, regarding the limitations of statistical hypothesis testing.

Chapter 6

Conclusions and future work

The main results of this thesis concern the benefits of heavy truck ESC. In a simulator study with professional truck drivers, it was found that an on-market implementation of such a system reliably reduced skidding and control loss. Conventional methods for statistical analysis proved these effects in a novel instruction-based paradigm for repeated critical collision avoidance. Additional analyses, involving both statistical testing and driver modeling, provided indications that drivers' control strategies for vehicle stabilization in the repeated scenario were the same as in an unexpected critical scenario. This result has important implications in the area of active safety evaluation; replicating the study using experiments with larger number of drivers appears recommendable. Here, the result has been used to argue that the observed benefits of heavy truck ESC should be present also in unexpected critical situations, a hypothesis for which this thesis may thus provide the strongest evidence to date.

Variations in behavior between drivers has been another object of study. The simulator study confirmed previous findings of decreasing reaction times to hazardous events with increasing driving experience. A possibly novel contribution was the demonstration that drivers who collided instead of applying steering avoidance (something which has been observed also in previous research) may have done so because of very long reaction times to steering, rather than because of a complete inability of exhibiting critical steering collision avoidance. Continuing with the theme of behavioral variability, the question of whether ESC is equally useful for all drivers has also been addressed to some extent. The statistical analyses suggested that, at a group level, novice drivers had a larger benefit of ESC than experienced drivers. Preliminary illustrations have been provided regarding how closed-loop simulation with driver models can be used to investigate such effects in more detail, even at the level of individual drivers.

Another central part of this thesis has been an extensive literature review of driver models applicable in such simulation-based research. An important insight from the review was that even though there exists a very large number of competing and seemingly different models, actual behavior may not always vary as much between models as the model equations may appear to suggest at a first glance. Furthermore, it was found that the ability of existing driver models to reproduce the behavior of human drivers in the relevant crash scenarios has only been investigated for very few models. Therefore, increased efforts regarding model validation and comparison can be recommended.

Here, in what may be the first successful parameter-fitting of a driver model to unexpected critical steering behavior, some validation has been provided of the two-point visual control model of steering, originally proposed by Salvucci and Gray [77]. However, the fitted models failed to generalize to situations with less severe steering. Extending the Salvucci and Gray model with satisficing capabilities is suggested as a possible means of improving its generality. Other possible directions of future work include comparison of the model's performance with that of other models, as well as empirical work with the potential of disproving the model's underlying assumptions. Also, mathematical derivations have been provided that link the model's far point control behavior to vehicle dynamics, leading to some specific predictions of how this control behavior may be affected by vehicle properties and vehicle speed. These predictions could be tested experimentally, and similar mathematical derivations could also be attempted for the near point control behavior of the model.

Finally, another important future challenge is to verify that the stabilization steering behavior observed here is not specific to the driving simulator context. If drivers can be shown to exhibit this type of behavior also in response to yaw instabilities of a real vehicle, this would provide even stronger evidence for the benefits of heavy truck ESC. It would also provide further support for the idea presented here, that it may be possible to improve current ESC systems by replacing their driver models with something more similar to the Salvucci and Gray model.

This possible potential for improvement could not easily have been identified on the test track, at least not with the methods typically used today. In that sense, this thesis has also provided an illustration of the importance, for developers and testers of active safety systems, of properly studying the behavior of real drivers, in the near-accident situations being targeted.

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Paper I

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

Accident Analysis and Prevention 50, pp. 1266–1277, 2013.

Paper II

DRIVER BEHAVIOUR IN UNEXPECTED CRITICAL EVENTS AND IN REPEATED EXPOSURES – A COMPARISON

submitted to

European Transport Research Review.

Paper III

A review of near-collision driver behavior models

Human Factors: The Journal of the Human Factors and Ergonomics Society 54(6), pp. 1117–1143, 2012.