

THESIS FOR THE DEGREE OF LICENTIATE OF ENGINEERING

in

Machine and Vehicle Systems

DRIVER MODELING: DATA COLLECTION,
MODEL ANALYSIS, AND OPTIMIZATION

OLA BENDERIUS

Department of Applied Mechanics
CHALMERS UNIVERSITY OF TECHNOLOGY
Göteborg, Sweden 2012

**Driver modeling: Data collection,
model analysis, and optimization**
OLA BENDERIUS

© OLA BENDERIUS, 2012

THESIS FOR LICENTIATE OF ENGINEERING no 2012:11
ISSN 1652-8565

Department of Applied Mechanics
Chalmers University of Technology
SE-412 96 Göteborg
Sweden
Telephone: +46 (0)31-772 1000

Chalmers Reproservice
Göteborg, Sweden 2012

*To the World,
which I can faintly hear outside my window.*

Driver modeling: Data collection, model analysis, and optimization

Ola Benderius

Department of Applied Mechanics

Chalmers University of Technology

Abstract

This thesis concerns aspects of driver modeling, with an emphasis on critical near-crash scenarios, involving time spans of around 10 s of driving. Here, driver modeling has been studied using both computer simulations and experiments carried out in a high-fidelity driving simulator.

A computer simulation environment has been developed especially for driver modeling. This simulation environment includes a stochastic optimization method for model parameter tuning. Moreover, a review of existing driver models has been carried out. In many cases in the literature, new driver models have been proposed without comparison with existing models. Many models also lack proper validation against driving data. A possible explanation may be that such data are expensive and difficult to collect, especially in critical scenarios.

However, in this thesis, the results obtained in a driving simulator study involving a collision avoidance scenario indicate that, at least to some extent, data collected in *repeated* exposures to a critical event resemble, in many important aspects, data obtained in an unexpected exposure to the same event. Thus, using repeated exposures in a careful manner, one can obtain much larger amounts of available data. In the particular case considered here, the steering behavior was largely conserved between exposures. With increased amounts of data, it becomes possible to carry out formal optimization of driver models (using, for example, the simulation environment presented here) without overfitting model parameters to noise in the data.

Keywords: driver modeling, driving simulator, simulation software, genetic algorithm, stochastic optimization

Acknowledgements

I would like to thank the QUADRA project for funding the research presented in this thesis. I am grateful for the valuable help and expertise from all project participants. In particular, I would like to thank my fellow PhD student and friend Gustav Markkula for many stimulating discussions, and the essential introduction to the field of traffic safety.

My progress as a young researcher would not have been possible without help from my great supervisors, Dr. Mattias Wahde and Dr. Krister Wolff. Their tremendous support, valuable insights, and inspiring words have led me to where I am today. For that, I am most grateful.

I would also like to acknowledge Eva Åström, Jesper Sandin, Martin Fischer, and the other staff at VTI for being so friendly and such a great help during the eLKA experiment. A very special thanks goes to Bruno Augusto for giving even more, and for covering me on the battlefield.

Finally, I would like to thank my coworkers at the VEAS division for a superb working environment, my family and friends for their personal support, and especially my dear wife Lisa for her unconditional love.

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., *A review of near-collision driver behavior models*. Human Factors: The Journal of the Human Factors and Ergonomics Society, 2012, *in press*.
- II. Benderius, O., Markkula, G., Wolff, K., and Wahde, M., *A simulation environment for analysis and optimization of driver models*. In: V. Duffy (Ed.): Digital Human Modeling, Proceedings of HCII 2011, LNCS 6777, pp. 453–462, 2011.
- III. 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*. Submitted to Accident Analysis and Prevention.
- IV. 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.

Technical terms used in the thesis

active safety, 1
adaptation, 36

behavior perspective, 5
bicycle vehicle model, 19

cognitive perspective, 5
computer simulation, 2
control modes, 36
control perspective, 5
crossover model, 7

data mining, 11
data points, 13
double lane change, 25
driver model, 2
driver model parameters, 2
driver type, 36
driving simulator, 1

electronic stability control, 12
emergency lane keeping assist, 14
expectancy, 11

field-operational tests, 11

genetic algorithm
 crossover, 22
 fitness, 21
 initialization, 22
 mutation, 22
 selection, 22
genetic programming, 22

intelligent vehicle systems, 3
intervening systems, 3

looming cues, 9

operator, 5
optimal control, 7

passive safety, 1
plant, 5
preview, 6

retinal flow, 9

safety benefit, 1
satisficing, 8
schemata, 10
signal, 23
stochastic optimization, 17
 ant-colony optimization, 21
 generation, 22
 genetic algorithm, 21
 hold-out validation, 22
 individual, 21
 overfitting, 22
 particle swarm optimization, 21
 population, 21

test track experiments, 11
time series, 23
time step, 5

visual direction, 9

Table of Contents

1	Introduction and motivation	1
1.1	Active safety systems	3
1.2	Scope and contributions	4
2	Designing driver models	5
2.1	Control perspective	5
2.2	Behavior perspective	7
2.3	Cognitive perspective	8
3	Collecting data for driver models	11
3.1	Case 1: A lead vehicle braking scenario	12
3.2	Case 2: A head-on collision scenario	14
4	Simulation environment	17
4.1	Simulation	17
4.1.1	Scenario and simulation handler	17
4.1.2	Vehicle models	19
4.2	Optimization	20
4.2.1	Method	21
4.2.2	Optimization handler	23
5	Tuning driver models	25
5.1	Scenario setup and data collection	25
5.2	Driver model selection	27
5.3	Driver model tuning	27
5.3.1	Model evaluation	28
5.3.2	Parameter optimization	30

6 Discussion	33
6.1 Selecting a suitable model design	33
6.2 Collecting data in repeated exposures	34
6.3 Validating driver models	35
7 Conclusions and further work	37
7.1 Conclusions	37
7.2 Further work	38
Bibliography	41
INCLUDED PAPERS	

Introduction and motivation

In a recent survey [45], the number of worldwide road traffic fatalities was estimated at over one million. Naturally, road traffic accidents constitute a global problem that causes large social and economical costs. Even though traffic safety involves, for instance, cultural, legal, and infrastructural aspects, it is also closely related to vehicle safety. When working with vehicle safety, a common distinction is between **passive safety**, such as vehicle design, seat belts, or air bags, and **active safety**, such as the use of radar and cameras for predicting dangerous situations, or autonomous control.

By analyzing accident statistics researchers have shown that some safety systems have brought significant reduction in traffic injuries and fatalities [33]. However, in many cases, especially regarding active safety, an estimate of the **safety benefit** of the system is desired before it is put into production [27, 44]. Generally, it is problematic to evaluate vehicle safety systems in order to get a good enough approximation of the safety benefit, mainly due to the complex traffic environments where the systems are applied. In order to carry out sufficient evaluation covering all relevant traffic scenarios, many tests are typically required. This is a problem since traditional vehicle experiments, such as crash tests or test track driving, often involve high economical costs. In addition, there might be various safety risks involved in cases where the driver must be included in the evaluation process.

As a replacement or a complement to traditional vehicle tests, **driving simulators** can be used in order to avoid exposing drivers and vehicles to danger. Driving simulators typically consist of a vehicle cabin mounted on a moving platform. By using the platform together with visual and auditory representations, test subjects can be studied in rather complex traffic environments, with high repeatability and with good data logging opportunities. Recently, several active safety systems, both prototypes as well production

models, have been evaluated in various simulator studies [37, 43]. Two such studies are also described in this thesis. One of these studies is further analyzed in Papers III and IV. However, conducting experiments in driving simulators is, like the traditional tests, very costly.

Computer simulations can be used as a way to avoid problems related both to risk and economical costs. Such simulations are typically used as a complement to other vehicle tests (in real vehicles, or driving simulators). In computer simulation, the vehicle and the driver can be evaluated in various critical situations. However, simulating the driver requires a **driver model**. A review of driver models can be found in Paper I. The purpose of contemporary driver models is typically to predict driver control inputs, such as steering or braking, in specific scenarios. Typical examples of scenarios where driver models are currently used include (i) lane keeping in normal driving conditions [8], (ii) vehicle evaluation maneuvers [4], (iii) collision avoidance [13], and (iv) optimal driving at race tracks [36]. Depending on the scenario under study, the driver model might be designed to capture driver aspects, such as experience or attention, as **model parameters** [41]. Different drivers can then be simulated using different parameter values. By also varying vehicle and scenario parameters, a large number of different test settings can be studied without the problems associated with other vehicle tests. However, computer simulations may not accurately capture all aspects of vehicle dynamics and driver behavior. Thus, as mentioned above, computer simulations should be used to complement, rather than to replace, tests with real vehicles and driving simulators.

Computer simulations of drivers and vehicles can be approached in different ways. In this thesis the approach has been to collect data from experiments involving real drivers, and then to use the collected data when developing driver models.

This thesis addresses the topic of driver modeling, by considering the three phases of: (i) model design, (ii) data collection, and (iii) parameter tuning. The main focus is on driver models of collision avoidance in near-crash situations, typically defined as events requiring rapid evasive maneuvers from the driver. By modeling driver control inputs in these situations, one may gain a deeper understanding of the processes involved, knowledge that can later be used for developing and evaluating a variety of safety systems aimed at avoiding traffic accidents or, at least, reducing their severity.

All papers included in this thesis consider different aspects of driver modeling. Paper I presents a review of driver models applicable in collision avoidance scenarios. Papers III and IV deal with the collection and analysis of data applicable to driver model development. Both papers are based on data collected in a driving simulator study, involving truck driving on slippery

roads. Paper III is focused on driver properties, such as experience, and their effect on driver behavior, while Paper IV deals with the validity of within-subject repeated exposures to a critical scenario. Paper II describes a computer simulation software environment developed (mainly by the author) especially for driver modeling. The simulation environment can be used for simulating driver models as well as tuning their parameters using stochastic optimization methods (further described in Sect. 4.2). The environment was also used in the model comparison presented in Paper I.

1.1 Active safety systems

The recent development of in-vehicle computers and sensors, such as radar and cameras, has made possible the introduction and development of **intelligent vehicle systems** (IVS). In the last two decades, efforts to develop and evaluate such systems have been extensive and widespread [3]. Active safety systems, a category of systems within IVS, take action in crash and near-crash situations by helping the driver to avoid an accident or, at least, reduce its effects. Examples of situations where active safety systems are used include lead vehicle braking, lane departure, and loss of control scenarios. In such situations, common interventions from active safety systems include auditory, visual, or tactile warnings as well as autonomous braking or steering. Systems that temporarily take control of the vehicle are referred to as **intervening systems**.

Driver behavior is a very relevant factor when it comes to the effectiveness and benefit of an active safety system. Situations where drivers come in conflict with the systems (e.g. do not comply with the intervention) are of particular interest. Generally, conflicts between the driver and the safety system may arise when a system (i) gives a warning or (ii) temporarily engages in autonomous control of the vehicle. A possible conflict regarding warnings is when the driver does not understand the warning, and could therefore be startled or confused. Furthermore, an active safety system could be calibrated in such a way that, in some cases, it would give warnings even in non-critical situations (i.e. false warnings), which might decrease the driver's confidence in the system. The same argument also holds for intervening systems, but with the addition that the driver and the system could be in conflict during the intervention itself, thus creating new safety concerns. For example, if the driver does not have the same understanding of the situation as the safety system, he or she might want to counteract the intervention [37].

After gaining a better understanding of driver behavior, and creating

models thereof, one can then use computer simulation in order to study the system–driver dynamics and the potential safety benefit of active safety systems, thus making possible further development of technology used in improvements of traffic safety.

1.2 Scope and contributions

As mentioned above, driver models have a large potential in aiding the development and evaluation of active safety systems. This thesis is focused on the practical aspects of data collection as well as design and optimization of driver models, rather than the application of such models, a topic that will be considered only briefly. The text has been structured in a step-by-step manner based on three phases: (i) model design, (ii) data collection, and (iii) model tuning.

The author was the main contributor to Papers II and IV, and one of two main contributors to Paper I. The author’s contributions to Paper III have been more limited.

Designing driver models

For the design of a driver model, a specific scenario is typically considered. Examples of such scenarios are lane keeping, double lane changes, or evasive maneuvers. Depending in the scenario at hand, the driver model is required to generate different types of control inputs to the vehicle. Two categories of such control inputs are steering and braking behavior. Steering behavior is typically given as a steering angle for each time step¹, and braking behavior is typically represented, for each time step, as a deceleration value.

Looking at the variety of driver models discussed in Paper I, it is clear that such models cover a large range of different purposes, and are based on different underlying theories of human behavior. When discussing different driver models from a design point-of-view it is useful to categorize models according to their structure. From Paper I, at least three different design perspectives can be identified: (i) a **control perspective**, (ii) a **behavior perspective**, and (iii) a **cognitive perspective**.

2.1 Control perspective

Historically, the first driver models of steering were based on control theory [14]. Similar models had, however, been used earlier in aviation and in military applications [23, 39]. Still today, many of the new driver steering models are based on control theory. From this perspective the human driver is considered as a controller (or an **operator**) and the vehicle is considered as a **plant**. If the system is defined as a closed control loop as illustrated in

¹Computer simulations of vehicles and drivers typically involve a large number of coupled differential equations, which are discretized and integrated using a **time step** which typically is of order 0.01 s.

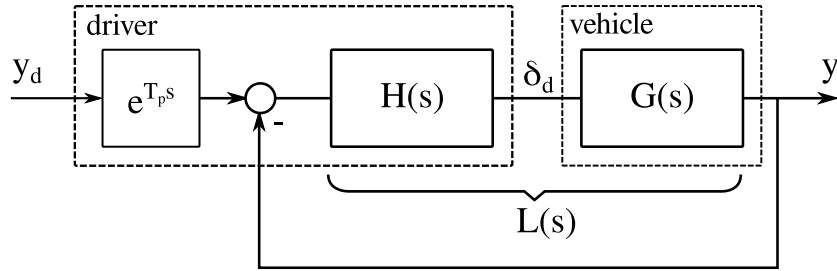


Figure 2.1: A closed-loop driver-vehicle system, where $H(s)$ is the controller, $G(s)$ the plant, $L(s)$ the controller-plant combination, T_p the preview time, δ_d the driver steering action, and y and y_d are the actual and desired lateral positions, respectively.

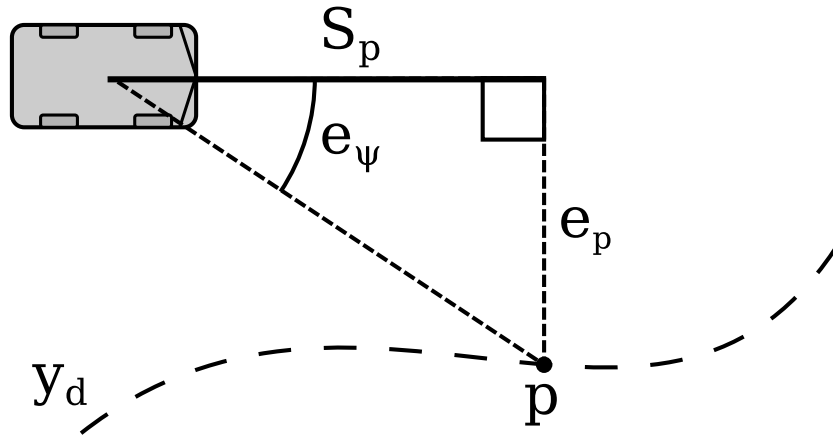


Figure 2.2: The preview points p is projected onto the desired path y_d , by using the preview distance S_p . The preview distance is calculated from a preview time according to Eq. (2.1). The errors e_p and e_ψ are typically used as inputs to the driver model.

Fig. 2.1, methods from control theory may be applied.

An important concept in most steering models is that of **preview** (see Figs. 2.1 and 2.2), the purpose of which is to obtain future values of the desired path, so that upcoming curves can be detected and negotiated. Driver models might have one or several preview points, each defined by a preview time T_p according to

$$S_p(t) = \dot{x}(t)T_p \quad (2.1)$$

where \dot{x} is the longitudinal speed and $S_p(t)$ a varying distance to a point in front of the vehicle. The driver model often uses deviations in lateral position or yaw angle, as seen in Fig. 2.2, in order to calculate a corrective steering action. A simple example of a control theory model that only uses

the heading error [32, 20] is given by

$$\delta(t) = K\epsilon(t - T_R) \quad (2.2)$$

where $\epsilon(t)$ is the angle between the vehicle heading and the preview point, T_R the driver reaction time, and K a gain constant.

A benefit of looking at drivers as controllers is that methods from control theory can be applied directly in the model. Examples are driver models that optimize their behavior according to predefined cost functions by using **optimal control** [21]. In each iteration of the simulation, a cost function is optimized over a preview interval. A typical cost function, when generating steering control for a vehicle dynamics model, would involve minimization of deviations from the desired path. Race track driver models use this approach in order to find the most efficient way of driving around a race track [36]. However, there are models that, apart from minimizing deviations from the desired path, also include driver comfort aspects such as limits to lateral acceleration and engine speed in the cost function [29]. In Paper I, a comparison between some of the mentioned models can be found.

Even though control theory driver models typically are focused on following a desired path as closely as possible, there are models describing more general aspects of the human driver. One such model is the often cited **crossover model** [24], defined as

$$L(s) = \frac{\omega_c}{s} e^{-\tau s} \quad (2.3)$$

where $L(s)$ is the combined driver and vehicle system as seen in Fig. 2.1, ω_c is the crossover frequency², and τ a time delay. The model, also referred to as the man-machine model, approximates a closed-loop behavior for the linear open-loop transfer function $L(s)$. Even though the model only contains two parameters, it has been successfully used to approximate control behavior in a large number of system environments [25].

2.2 Behavior perspective

As stated above, driver models designed from a control perspective have some benefits associated with them. However, when creating a model based on observed or hypothesized driver behavior other design modes might be more suitable.

²The frequency where no amplification of the input occurs ($L(j\omega) = 0\text{dB}$).

Many models of longitudinal control are designed from a behavior perspective. Such models typically try to capture observed behavior by complying to a few simple rules. For example, the GHR³ model [7] (described further in Paper I) aims to capture observed behavior when a vehicle is following a lead vehicle. The model is defined as

$$\ddot{x}(t) = \lambda \Delta \dot{x}(t - T_R) \quad (2.4)$$

where $x(t)$ is the longitudinal position of the following vehicle, $\Delta x(t)$ the distance between the two vehicles, T_R a time lag, and λ a sensitivity term defined as

$$\lambda = a \frac{\dot{x}^m(t)}{\Delta x^l(t - T_R)} \quad (2.5)$$

where a , m , and l are constants. Dots denote differentiation with respect to time. Eq. (2.4) results in the behavior of keeping the same speed as the lead vehicle, and Eq. (2.5) results in swifter speed corrections at higher speeds or when the lead vehicle is closer. Even though the GHR model is relatively simple, it can represent complex behavior, especially when simulating a system with several vehicles each controlled by the model. As described further in Paper I, the model has been used in many different applications and has in some cases been modified in order to capture scenario-specific behavior, such as collisions [47].

There are some driver models of lateral control designed from a behavior perspective as well. One such model, intended for evasive steering [13], is defined as

$$\delta(t) + K_1 \dot{\delta}(t) = K_2 \Delta y(t - T_R) \quad (2.6)$$

where $\delta(t)$ is the vehicle steering angle, Δy the lateral displacement of an obstacle, T_R the reaction time, and K_1 and K_2 are constants.

A concept related to the behavioral perspective is the one of **satisficing** models, as discussed in Paper I. Rather than following a desired path, as typical from a control perspective, a satisficing model instead generates behavior which is *good enough* for the current situation [8, 48]. For example, a satisficing driver model would only correct the current speed or path if they venture outside predefined safety regions.

2.3 Cognitive perspective

Driver modeling can also be approached from a cognitive perspective, using models of the human mind as a framework. In many ways, this approach

³Named after its authors: Gazis, Herman, and Rothery.

is more difficult to apply than the other two perspectives mentioned above, the reason simply being that little is known about how the mind actually works. Therefore, models from this perspective are often only applicable to very specific driver phenomena observed in traffic. Still, as exemplified below, such models generally *explain* driver behavior in a way that makes them applicable in a large number of scenarios.

For instance, it would be relevant to know *why* drivers brake harder at higher speeds and shorter headway as predicted by the GHR model (described above). As stated in Paper I, even though much effort has been put into finding realistic parameter values for the GHR model, good values have not yet been found. This is an indication that, even if a model shows a qualitative good behavior, it might not be possible to tune it correctly using real world data. If useful parameter values cannot be found, one may conclude that the model is simply not good enough for the general case. However, by incorporating knowledge regarding the motivation for specific driver behaviors, one may be able to improve the model.

A cognitive phenomenon, namely sensitivity to looming (or **looming cues**), could potentially be used when tuning or redefining the GHR model. In this context, looming refers to the optical expansion of an object in the driver's field of view, when the object is moving towards the driver. It has been shown that looming cues can trigger attention and reflex responses from a driver [19]. As mentioned above, models defined from a cognitive perspective cannot, perhaps, be used in a standalone fashion, but could be used as a part of a model or in order to validate the behavior of a model.

Another cognitive (or rather perceptual) model uses the perceptual properties of **visual direction**, and **retinal flow** in navigation (e.g. negotiating a curve) [42]. The visual direction can be explained as a target point in the visual field. In a driver model context, the visual field can be considered as the windshield of a vehicle. For instance, when moving straight towards a visual direction positioned in the center of the visual field, the visual direction will remain stationary. However, when moving towards a visual direction positioned to the left in the visual field, the visual direction will rotate counterclockwise. The retinal flow can be explained as the motion of the perceived features, such as colors and objects, projected on the retina. In order to capture human navigation, the model tries to accomplish two things: (i) minimizing the movement of the visual direction, and (ii) minimizing the rotation in the retinal flow. The model is defined as

$$\ddot{\theta} = k(\beta_1\psi + \beta_2\gamma) - b\dot{\theta} \quad (2.7)$$

where $\ddot{\theta}$ is the angular acceleration, ψ the retinal flow, γ the visual direction, and where k , β_1 , β_2 , and b are constants. In a driver model context, the

visual direction is defined as the angle between the vehicle's yaw angle and the driver's gaze.

Cognitive properties such as looming cues and navigation by visual cues have, at least to some degree, general validity, and can therefore be studied and parameterized in experiments not necessarily related to driving. For instance, when walking or riding a bike, the same kind of visual cues as when driving a car might be used [42]. Thus, knowledge gained in other fields, such as psychology, can to some extent be incorporated into driver models as well.

There are also models that try to explain certain specific driver properties. One such property, relating to driver comfort, is a relationship between the lateral and longitudinal accelerations chosen by a driver [46]. This property is rather general, and can therefore be used in many different driver modeling situations, for instance when validating a driver model.

The cognitive models discussed so far model limited observed cognitive phenomena. There are, however, models that try to capture cognitive aspects in a more general way. Some of these models use the **ACT-R** (atomic component of thought-rational) framework for cognitive modeling [2]. In this framework, factual knowledge as well as procedural knowledge can be represented. This kind of model has, for example, been used when modeling driver distraction [35].

Another, more general, model explains, from a cognitive point of view, why accidents occur, using the concept of **schemata** [6]. In cognition, schemata try to capture, for instance, that certain traffic situations (e.g. an overtaking) correspond to certain actions from the driver. The model states that accidents occur when, for the current situation, an improper schema is selected by the driver.

Collecting data for driver models

There are different types of data sources relevant to driver modeling. The most common ones include (i) **test track experiments**, (ii) driving simulator experiments, and (iii) **field-operational tests (FOTs)**. They all have their strengths and weaknesses and are therefore suitable for different modeling purposes. As mentioned in Chapter 2, driver models are often designed for a specific scenario. Therefore, data collected for driver modeling typically also target a specific scenario.

Since driving simulators rely on simulated vehicles, the fidelity of the vehicle dynamics might be lower compared to real vehicles used in test track experiments or FOTs. However, as discussed in Chapter 1, an important benefit of driving simulators is that they do not expose vehicles or drivers to any risk during experiments. Another benefit is that driving simulators allow for controlled experiments to a very high degree, which is especially important when it comes to critical scenarios with small margins (e.g. precise timing of events).

In FOTs, the subjects use vehicles, equipped with data logging devices and cameras, on normal roads. The vehicles are not used for a specific test, but instead for every day driving for an extended period of time. Therefore, FOTs differ from both test track experiments and driving simulator experiments in the sense that they do not allow for controlled experiments at all. Instead, they rely on subsequent **data mining** where sufficiently similar scenarios can be used for analysis of a given safety problem. A drawback with such an approach, however, is that naturally rare scenarios generally are hard to study.

The concept of **expectancy** is central in the study of human behavior in specific situations. In this context, expectancy refers to the subject's belief that something unusual will happen. For drivers participating in a driving

simulator experiment, expectancy is likely to be high since the subjects are placed in a highly unusual environment, and are asked to act within a virtual reality. For normal drivers, expectancy will most likely be high in test track experiments as well, due to the unfamiliar environment and the fact that they are studied while driving an instrumented car. By contrast, a unique feature of FOTs is that they induce very low expectancy since the drivers use the same vehicle for a long period of time in unspecific situations. As a way to validate behavior from experiments involving high levels of expectancy, one could use data from FOTs, if available [31].

It might be argued that realism is an important factor when collecting data for use in driver modeling, implying that data collected at test tracks or in FOTs are better suited than data collected in driving simulators. However, in many cases, especially when studying critical situations, the driving simulator is preferred simply because it makes it possible to use unrealistic (but necessary) scenario elements. For example, when studying rare critical situations it might be very difficult to get subjects into the situation in a fully realistic setup. A typical simple solution in a driving simulator would be to change something in the environment when the subjects are looking away.

Two different driving simulator experiments are described below, the first involving trucks, and the second passenger cars. Both experiments consider driver behavior in an active safety context.

3.1 Case 1: A lead vehicle braking scenario

In order to evaluate an active safety system for trucks, an experiment involving a lead vehicle braking scenario was carried out. The system, most commonly known as **electronic stability control** (ESC), is designed to reduce yaw instability during skidding. When the system detects instability, by comparing the steering wheel angle with the vehicle's direction of velocity, it brakes wheels individually in order to increase stability. Typically, the system brakes the outer front wheel to reduce oversteer, and the inner rear wheel to reduce understeer [30]. Situations where the risk of instability is high occur when drivers carry out rapid maneuvers while driving at high speeds on slippery roads. An example of such a situation is a lead vehicle braking scenario, as illustrated in Fig. 3.1. Such scenarios could, if unexpected, trigger high speed lateral maneuvers and potential yaw instability. It has been found that about 19% of all truck crashes in the U.S. involve loss of yaw or roll stability, and could therefore be targeted by ESC [16].

For the experiment, a lead vehicle braking scenario on a slippery road was

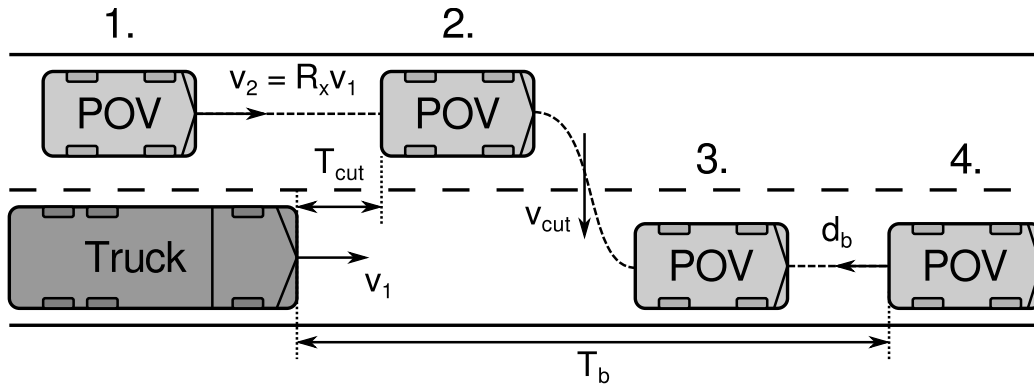


Figure 3.1: *The critical scenario under study in the ESC experiment. The truck, driving at speed v_1 on a slippery two-lane highway, is overtaken by a passenger car (the principal other vehicle, POV). Unexpectedly, the POV brakes hard with deceleration d_b , forcing the truck driver to initiate an evasive steering maneuver on the slippery road surface. A detailed description of the parameters can be found in Papers III and IV.*

implemented in a driving simulator¹. The main purpose of the experiment was to study the effects of driver experience on the ESC system performance. Two groups of drivers with different levels of experience (high and low, respectively), each containing 12 test subjects, were included in the study. Without any prior knowledge about the experimental setup, each subject started by carrying out simulator training involving both steering and braking. After the training, the subject was told that the actual experiment was about to start. After driving for a few minutes, the subject was exposed to an unexpected lead vehicle braking scenario, as seen in Fig. 3.3. From each experience group, six subjects had the ESC system activated during the critical scenario. Detailed information about the experiment can be found in Papers III and IV.

Creating a driver model, capturing both realistic steering and braking behavior, only based on the 24 **data points**² acquired from the unexpected scenario would probably be impossible. In fact, the effective number of data points would be even smaller, since many of the subjects did not even attempt to avoid the accident by using the steering wheel (see Paper III). Since it was hypothesized from the beginning that some subjects would not end up in ESC relevant maneuvering as a result of the unexpected event, the same critical

¹The Sim II truck simulator at The Swedish National Road and Transport Research Institute (VTI).

²In this context, the term *data point* is used as a shorthand for all the data collected during one repetition of a driving scenario.

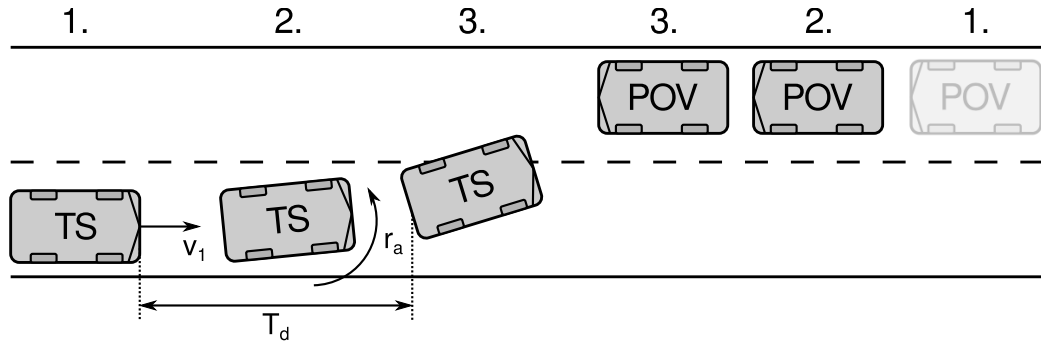


Figure 3.2: *The critical scenario under study in the eLKA experiment. The driver under study (test subject, TS) drives at speed v_1 , unaware of the oncoming vehicle (POV) driving at the same speed. During distraction, the TS, still unaware of the oncoming car, drifts towards the opposite lane. The eLKA system gives an intervention in order to steer the TS back to the original lane.*

scenario was repeated 12 more times (6 times with the system, and 6 times without) as a second part of the experiment. However, in the second part, each subject was instructed precisely on what would happen, and on which actions they were supposed to take. The concept of repeating critical driving scenarios is discussed in detail in Paper IV. In a third and final part of the experiment, the subjects were instructed to carry out double lane changes on a simulated test track. The double lane change was designed to mimic the severeness of the lead vehicle braking scenario.

3.2 Case 2: A head-on collision scenario

In an experiment involving a head-on collision scenario, a prototype of an active safety system was evaluated. The system is called **emergency lane keeping assist** (eLKA) and is designed to help the driver to avoid collision with cars in other lanes. When the system detects a critical situation, by measuring the distance to surrounding vehicles and lane boundaries, an active steering wheel intervention is given in order to avoid the threat. Typically, the critical scenario could involve a potential head-on collision with an oncoming car, as illustrated in Fig. 3.2. Such scenarios could be the result of distraction, causing inattention as well as drifting. According to accident statistics, while only around 2% of all accidents (in the US) are classified as head-on collisions, this type of accident still accounts for over 10% of all fatalities [26].

For the experiment, a head-on collision scenario was implemented in a



Figure 3.3: *Left panel: A snapshot from the unexpected scenario in the ESC experiment, where a truck driver is forced to carry out rapid maneuvers on a slippery road. Right panel: A snapshot from the unexpected scenario in the eLKA experiment, where a car driver looks away from the road at the same time as a collision course with an oncoming car is established.*

driving simulator³. The main purpose of the experiment was to measure the driver's initial reaction to an unexpected steering intervention given by the eLKA system. Two groups containing 20 test subjects each were recruited for the experiment. One group had their system activated during the critical scenario, and the other group did not have the system activated.

In order to get a subject into an unexpected head-on situation, as seen in Fig. 3.3, some special measures had to be taken. First, the subject was told that the purpose of the study was to evaluate a newly developed distraction task, in which numbers should be read from a display positioned between the front seats. Second, the oncoming car was visible only after the subject looked down towards the distraction task. Third, when the subject was looking down, an (unphysical) artificial yaw rotation was applied to the environment, without using the motion platform, in order to place the vehicles on a collision course. Fourth, cues usable in navigation during distraction, such as road markings and trees, were reduced or removed. Each subject started with a training session including non-critical overtaking maneuvers and practicing the distraction task. After the training, the subjects were instructed to drive at 90 km/h on a rural road where they would be exposed to the distraction task several times. Unbeknownst to the subjects, the unexpected head-on collision would be initiated during three of these distraction tasks towards the end of the drive.

Just as in the ESC experiment described above, scenario repetitions (with

³The Sim IV simulator (with the passenger car cabin) at The Swedish National Road and Transportation Research Institute (VTI).

prior instructions) were used. In this case, the distraction task was *not* used. Instead, the subjects were instructed to hold the steering wheel in zero position during the artificial yaw motion, and attempt to avoid the head-on collision only when the oncoming car blinked its headlights. For each subject, the scenario was repeated 12 times, each time using one of four different variations. Two of the variations corresponded to the eLKA system being either active or inactive during the critical event, and the last two variations corresponded to the system being either active or inactive, but with a delay of 0.2 s until the oncoming car blinked its headlights.

As a third and last part of the experiment, the driver's response to sudden steering wheel torques was tested further. While driving in the middle of a perfectly straight three-lane road, the subject was asked to carry out the distraction task several times. Occasionally, when the subject was distracted, a steering wheel torque was applied (as a step function) to the steering wheel for 0.7 s. The torque could be either 3, 4, or 5 Nm and directed either to the left or to the right. The instructions given to the subject were to directly abort the distraction task and change to the left or to the right lane (corresponding to the direction of the torque). In total, each subject was given 12 steering wheel torques.

Chapter 4

Simulation environment

The simulation environment, first described in Paper II, was developed by the author specifically for simulating and tuning driver models. The software has been written in the C# programming language, and uses the Ogre graphics library for visualization. In Fig. 4.1, two different views from the simulation environment are presented.

One of the most important features of the simulation environment is its capability to tune driver models using **stochastic optimization** (described below). Since such optimization algorithms require fast evaluations, the simulation environment has been developed with simulation speed as one of the main criteria. When run on a desktop computer, the software is capable of evaluating the outcome of a typical critical scenario over 100 times per minute. In this chapter, the various parts of the simulation environment will be described briefly.

4.1 Simulation

When setting up a simulation, one must first implement the scenario under study. The simulation environment was developed especially for simulating critical scenarios, and is thus intended for scenarios with a short time span (up to a minute), involving a few vehicles (up to ten). The simulation process and scenario definition will now be discussed.

4.1.1 Scenario and simulation handler

The scenario contains all road and environment definitions, as well as all simulated vehicles and their corresponding driver models. An example of a vehicle model is presented below, and an example of a driver model is

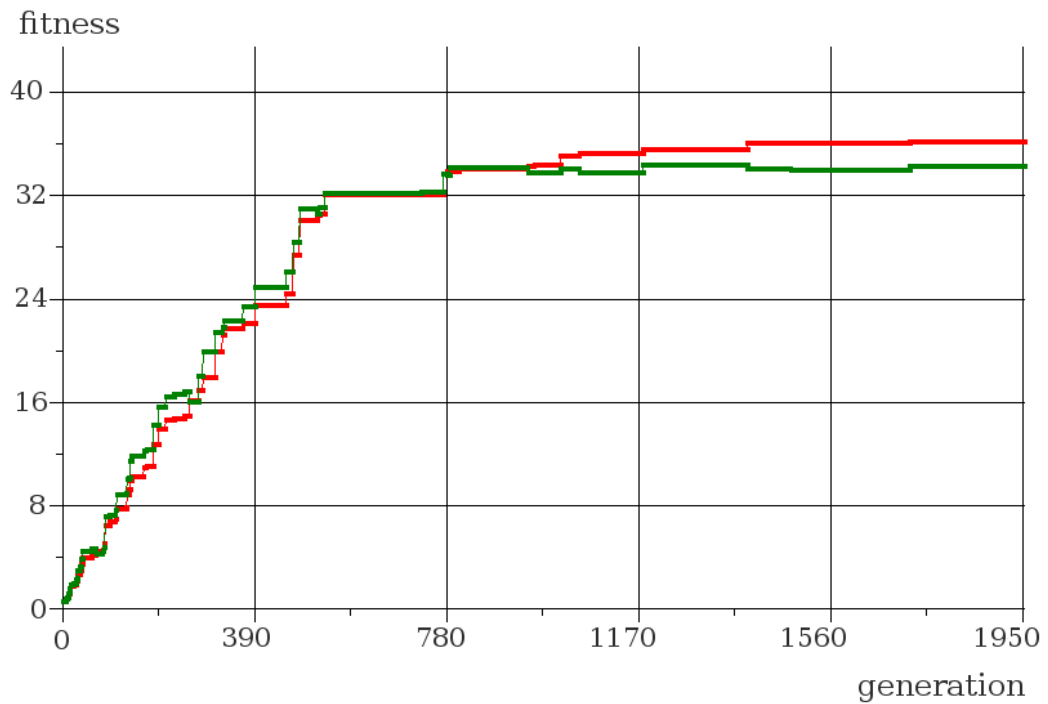


Figure 4.1: Two views from the simulation environment. Top panel: The visualization view. In this case, a passenger car is being driven towards road cones placed on a rural road. Bottom panel: The optimization view. The training fitness is shown in red, and the validation fitness (described in Subsect. 4.2.2) is shown in green.

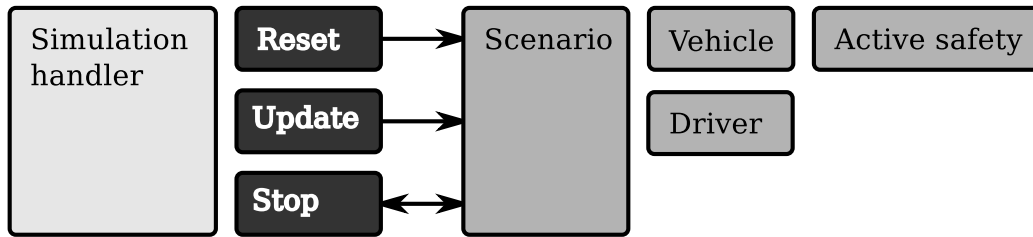


Figure 4.2: A schematic overview of the simulation process.

presented in Chapter 5. As illustrated in Fig. 4.2, the simulated vehicles may also contain various safety systems. In the context of driver simulation, the purpose of the safety system is normally to influence the behavior of the vehicle, the driver, or both, during a simulation, so that one can study the resulting actions taken by the driver model.

Three basic actions can be supplied to the scenario from the simulation, namely: *Reset*, *update*, and *stop*. When an action is applied to the scenario, it automatically propagates to any vehicle, driver, and active safety system within the scenario. The *reset* action sets all internal states to their initial values, typically before a simulation starts. Examples of such initial values include vehicle start positions, and driver initial brake pedal position. The *update* action increases the simulation time by one time step, resulting in evaluation of vehicle dynamics and driver behavior for that time step. Finally, the *stop* action terminates the simulation. The simulation handler is responsible for managing the time during the evaluation of a scenario, as illustrated in Fig. 4.2. However, note that the scenario can itself execute the *stop* action if any stop criterion (e.g. a time limit) is fulfilled in the current time step. Stop criteria can be defined specifically for each scenario, and might involve (apart from the time elapsed) any vehicle or driver property.

4.1.2 Vehicle models

As the main purpose of the simulation environment is to study (and optimize) *driver* models rather than detailed vehicle dynamics, one can, in many cases, use a simplified vehicle model, such as a **bicycle model** during a simulation. Such vehicle models ignore the width of the vehicle, treating each axle as one wheel. The main vehicle model used, so far, within the simulation environment was originally presented in [38]. The *kinematics* of that model

is given by

$$\begin{aligned}\dot{x} &= u \cos \psi - v \sin \psi \\ \dot{y} &= v \cos \psi + u \sin \psi \\ \dot{\psi} &= r\end{aligned}\tag{4.1}$$

where x and y represent the global position of the vehicle's center of mass (CM), u and v the local coordinate system fixed to the CM, ψ the yaw angle, and r the yaw rate. The *dynamics* of the vehicle model is given by

$$\begin{aligned}M(\dot{u} - vr) &= F_x - F_{yf} \sin \delta \\ M(\dot{v} + ur) &= F_{yr} + F_{yf} \cos \delta \\ I_z \dot{r} &= aF_{yf} \cos \delta - bF_{yr}\end{aligned}\tag{4.2}$$

where M is the vehicle mass, a and b the distance between the CM and the front and rear axle, respectively, and δ the vehicle steering angle. A steering wheel angle can be translated into a vehicle steering angle by $\delta = \delta_{SW}/G$ where G is the steering gear ratio. The lateral force F_x combines the brake and engine forces, and the forces F_{yr} and F_{yf} are the lateral rear and front forces, respectively, given by the often cited *magic formula* [28]

$$F_y = 2D_m \sin[C_m \arctan(B_m \alpha - E_m(B_m \alpha - \arctan(B_m \alpha)))]\tag{4.3}$$

where B_m , C_m , D_m and E_m are tire parameters, and the slip ratio is given by

$$\alpha_f = \frac{u \sin \delta - (v + ar) \cos \delta}{u \cos \delta + (v + ar) \sin \delta}\tag{4.4}$$

for the front axle, and

$$\alpha_r = \frac{br - v}{u}\tag{4.5}$$

for the rear axle. The vehicle model just described was used in Paper I when comparing the steering behavior of different driver models, in that case using the parameters listed in Table 4.1.

4.2 Optimization

The simulation environment can run a single scenario manually using a driver model with given parameters, something that is typically done for visualization purposes. However, normally, the simulation environment is used for optimizing driver models, in which case many sets of parameters are evaluated and visualization (i.e. real-time 3D rendering of the vehicles and their environment) is normally turned off for performance reasons. The optimization method will now be described briefly.

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

Table 4.1: *Vehicle model parameters used in Paper I.*

4.2.1 Method

In the literature, driver model parameters have most often been tuned by hand (see, for instance, [22, 8, 35, 36]). However, there are a few examples when optimization methods have been used instead. For example, in [49] a **genetic algorithm** (GA) was used for tuning the parameters of a PID regulator.

GAs [10] are a special case of a more general class of optimization algorithms referred to as evolutionary optimization methods. Such algorithms, in turn, belong to the class of stochastic optimization methods, a class that also includes for instance, **particle swarm optimization** (PSO) [15], and **ant-colony optimization** (ACO) [5]. The methods share the property that they all *search* for optima (maxima or minima) by using different stochastic operations. Furthermore, many stochastic optimization methods are inspired by biological phenomena. Generally, the operations are applied to a **population**, in which each member (referred to as an **individual**) constitutes a solution candidate for the problem at hand. The optimization methods are general and can be applied to any problem where an individual can be evaluated and compared to the performance of any other individual. The performance measure is commonly referred to as a **fitness measure** (a quantity to be maximized), in the case of evolutionary optimization methods.

Stochastic optimization algorithms have several advantages over classical optimization methods. For example, they are very general and can thus be applied without any need to simplify the system (e.g. a driver model or a vehicle model) being optimized. Furthermore, due to their stochastic nature, they are capable of avoiding to get stuck in local optima, a problem that affects some classical optimization methods.

A drawback associated with stochastic optimization is that, normally, one

cannot prove that an optimum found is a global optimum. However, when studying model behavior, one can most often define a *good enough* behavior for the application at hand.

In principle, one can also use a class of evolutionary methods called **genetic programming** (GP) to tune the structure (or design) of a model, not only its parameters. While this method has not yet been implemented in the simulation environment, it might be suitable for generating complex driver models, in situations where a closed-form mathematical formulation of a driver model cannot be found.

In the current version of the simulation environment, a GA has been chosen as the optimization method. Four basic operations are used by the GA: **Initialization**, **selection**, **crossover**, and **mutation**. In the initialization phase, a new random population containing N individuals is generated. In a driver modeling context, each individual might, for instance, represent a bounded parameterization of the model. After initialization, each individual is evaluated and assigned a fitness value based on its performance. Again, in a driver modeling context, this step could correspond to simulating the driver model in order to determine, for instance, how closely it will follow a predefined desired path using, say, the inverse of the mean absolute position error (relative to the desired path) as the fitness value.

Based on the fitness values, individuals are then selected for reproduction. In this phase, a new population (the next **generation**), still containing N individuals, is generated by repeated use of selection, crossover and mutation. Selection can be carried out using one of several different methods [40], all favoring individuals with high (relative) fitness values. In crossover, two selected individuals are merged, sharing their encoded parameter information among each other. When tuning a driver model, such exchange could mean that one or several model parameters are swapped between the two individuals. Finally, mutation is applied to the individuals by making small random changes before inserting them into the new generation. By repeating the entire process for many generations, the fitness of the best individual in the population will typically increase rapidly in the beginning, and then more slowly, often in a stepwise manner (i.e. such that a long period of constant maximum fitness is interrupted by a sequence of increases).

Since it is not possible to determine whether or not a given solution candidate represents a (local or global) optimum, a way to measure progress must also be considered. If the optimization is allowed to run for too long, one might eventually end up with the problem of **overfitting**. When tuning a model for too long, it will eventually capture irrelevant aspects of the data, such as noise or other artifacts. In order to avoid overfitting, **hold-out validation** (described in Paper II) can be used by splitting the available data

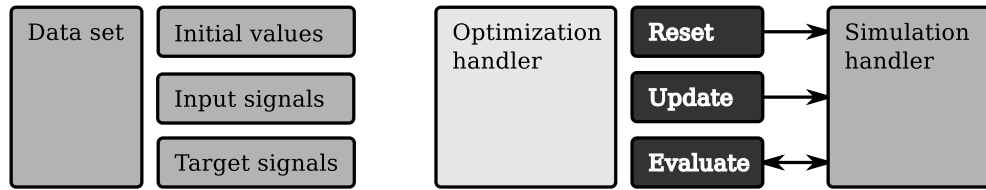


Figure 4.3: *Left panel: A schematic illustration of a data set used for optimization. Right panel: An overview of the optimization process.*

points into three parts, one larger part containing training data, and two smaller parts containing validation and test data. During optimization, the validation data is used only to control for overfitting. That is, the performance over the validation data is not provided to the optimization algorithm, but is used for determining when to stop the optimization process, namely at the point where the validation fitness reaches its maximum. After the optimization has been completed, the test data is used in order to test the solution on new (unseen) data.

4.2.2 Optimization handler

As mentioned above, the simulation environment includes a GA for the optimization of driver model parameters. The optimization process, illustrated in the right panel of Fig. 4.3, evaluates different driver model parameterizations by running successive simulations. When evaluating the model, one or several data sets are used. As illustrated in the left panel of Fig. 4.3, each data set contains initial conditions, input signals¹, and target signals. For each evaluated individual, each data set is used as follows: (i) the initial conditions are provided to the simulation (*reset*), (ii) in each time step, values from the input signal (e.g. vehicle speed) are assigned to the simulation (*update*), and (iii) the individual is evaluated by comparing the target signals (from the data set) to signals generated by the model (*evaluate*).

The overall fitness for the individual is calculated in three steps; (i) the fitness for each target signal within a data set, (ii) the combined fitness for all target signals within a data set, and (iii) the combined fitness for all data sets. When combining fitness values for several targets or data sets, one can choose whether to use the maximum measured error, the average error, or any other type of combined measure.

In order to determine when to stop the optimization, hold-out validation has been implemented and allows real-time monitoring of training and vali-

¹In this context, a **signal** corresponds to a **time series**.

validation fitness, as illustrated in Fig. 4.1. The validation fitness is calculated, for each generation, by evaluating the individual with the highest training fitness over the validation set. After the optimization has been completed, one can also evaluate the best individual using the test data.

Tuning driver models

As is evident, the behavior of a driver model depends on the values selected for its parameters. Typically, when a driver model is tuned (i.e. optimized) so that it can represent real driver behavior, its parameters are set using information obtained from driving data (see Chapter 3). The process of tuning a driver model will now be illustrated, using data from the experiment described in Sect. 3.2.

5.1 Scenario setup and data collection

The scenario considered here is a **double lane change** (DLC) maneuver. The same kind of maneuver was also considered in Paper II as part of a demonstration of the simulation environment and its optimization algorithm. In the demonstration, a simple open-loop steering model based on a sine function was tuned to carry out a DLC using a very small set of data, containing only three repetitions.

The DLC illustrated in this chapter differs slightly from the often cited **ISO double lane change** [12] and also from the DLC described in Paper II, in the sense that it is defined using only two barriers on a two-lane road, as illustrated in Fig. 5.1. Typically, DLCs are defined by three or more gates in order to get a high level of experimental control. In contrast, by instead using barriers, the drivers carrying out the maneuver are allowed to initiate the first lane change more freely, thus allowing for a higher degree of natural behavior throughout the scenario.

Driving data were collected as (a minor) part in the head-on collision simulator experiment described in Sect. 3.2. During the initial training session, the subjects were asked to carry out three successive DLCs (1.5 km

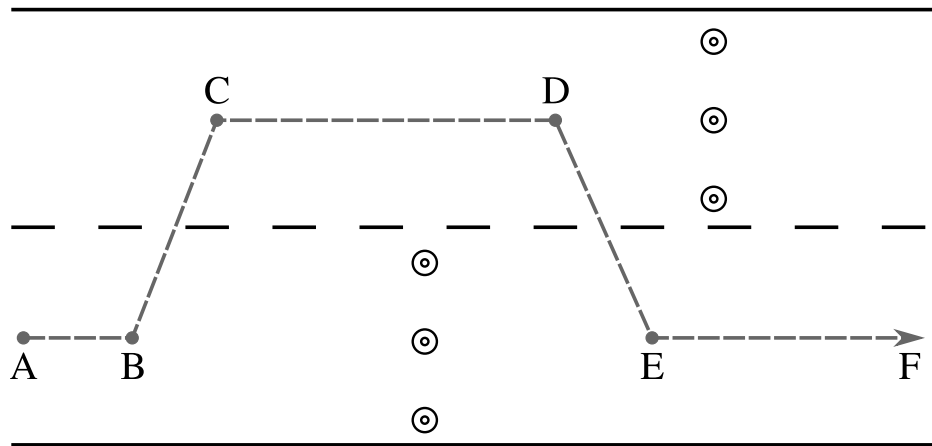


Figure 5.1: *The DLC scenario. The road cone barrier in each lane forces the driver to carry out the DLC, even though the initiation of the maneuver is chosen by the driver. The lanes are both 3.5 m wide. Points A through F illustrate the DLC as a path. The longitudinal distance from point A to the first barrier is 200 m, while the distance to the second barrier is 280 m.*

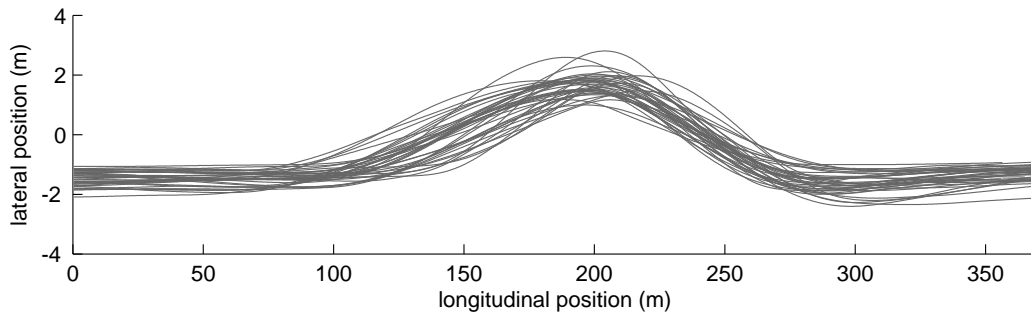


Figure 5.2: *The various vehicle trajectories extracted from the driving data.*

apart) at 90 km/h. The DLCs were each defined by two road cone barriers as described above. The test subjects were told to execute the maneuver as if overtaking another vehicle, without using the brakes. As explained to the test subjects, the purpose of the exercise was for them to experience the lateral dynamics of the simulated vehicle. However, in this simple illustration, only data from the second DLC maneuver will be used for tuning the driver model. Therefore, the number of data points will be equal to the number of participants, namely 40. However, due to technical difficulties, two of the data points were removed (leaving 38). The trajectories extracted from the driving data are shown in Fig. 5.2.

5.2 Driver model selection

Here, the multi-point preview model proposed by Sharp *et al.* [36] will be used for the DLC maneuver. The model was chosen since it is often cited and, moreover, was already implemented for Paper I. In the model, eight preview points are positioned at fixed preview times (see Eq. (2.1)), each defined as a fraction (0, 0.1, 0.2, 0.3, 0.4, 0.6, 0.8, 1) of the preview time T_p . The model uses a desired path in order to calculate a steering angle $\delta(t)$ according to

$$\delta(t) = K_\psi \psi_e(t) + K_1 y_{e_1}(t) + \sum_{i=2}^n K_i y_{e_i}(t) \quad (5.1)$$

where $\psi_e(t)$ is the heading error compared to the tangent of the desired path, $y_{e_1}(t)$ the vehicle's lateral deviation, $y_{e_i}(t)$ the lateral deviation of the preview points, and K_ψ , K_1 , and K_i are gain constants. In Paper I, the performance of the model was compared to that of several different steering models in a *single* lane change maneuver. In that particular comparison, the model carried out the maneuver with a distinct overshoot, arguably because the model was originally designed for race car dynamics.

When tuning the model, the preview time T_p , all the gains K , and the desired path are considered as free parameters. As for the tuning of the desired path, point *A* (see Fig. 5.1) is chosen as a fixed origin while the other five points (*B* to *F*) are tunable. In the original model, the gain terms as well as their total sum were assigned a specific saturation level in order to prevent the function from returning values that are too large. In the case considered here, however, since the model is tuned to a steering angle reference (i.e. the model is optimized towards realistic behavior) the saturation levels are not needed and were therefore omitted.

5.3 Driver model tuning

In the example considered here, the driver model tuning has been subdivided into two steps. First, the model was tuned to a few individual drivers to ascertain that it is, in fact, capable of representing the desired maneuver. Second, the model was tuned to represent an *average* driver by optimizing it using the whole set of data. In this case, an average driver represents an average behavior rather than any specific (median) driver, since the model was tuned so as to minimize the steering angle error over the entire data set (all drivers).

	1	2	3	A		1	2	3	A
T_p	2.195	0.469	0.643	1.420	x_B	88.212	199.947	98.134	117.962
K_ψ	0.026	0.002	1.030	0.036	x_C	202.598	356.021	195.677	158.987
K_1	0.007	0.011	0.009	0.020	x_D	278.845	448.994	209.489	214.916
K_2	0.004	0.004	0.001	0.004	x_E	450.079	608.188	383.428	379.348
K_3	0.002	0.023	0.024	0.004	x_F	584.111	786.701	581.500	452.828
K_4	0.002	0.001	0.004	0.013	y_B	-0.044	1.484	-0.287	0.987
K_5	0.014	0.016	0.011	0.005	y_C	4.445	0.164	2.027	2.586
K_6	0.091	0.004	0.008	0.012	y_D	1.131	0.664	0.534	1.392
K_7	0.003	0.005	0.000	0.002	y_E	2.841	0.822	-0.312	-0.069
K_8	0.006	0.004	0.020	0.004	y_F	4.525	4.533	0.253	1.482
ϵ	1.046	0.992	0.638	1.679					

Table 5.1: *Parameter values for the driver model after optimization. The columns denoted 1, 2, and 3 refer to the test subjects considered during model evaluation (see Subsect. 5.3.1), and the column denoted A refers to the average driver (see Subsect. 5.3.2). For the three individual subjects, optimization was carried out in order to evaluate the driver model design for the scenario under study. The average driver was generated by tuning the model to data from all 38 repetitions (26 for training, 6 for validation, and 6 for test). The x and y parameters correspond to the longitudinal and lateral positions (respectively) of points B through F (as presented in Fig. 5.1), measured (in meters) from from point A. The preview time T_p is given in seconds, and the gains K as well as the average (over time steps) steering angle error ϵ is given in degrees.*

5.3.1 Model evaluation

In order for the model to be able to represent an average driver in the DLC scenario, it must at least be able to capture the steering behavior of a single test subject carrying out the DLC maneuver. As a test, data from three subjects were selected randomly and were then used in three separate optimizations of the driver model (resulting in three different sets of parameter values, one for each driver).

The model was optimized using the simulation environment described in Chapter 4 and in Paper II. During optimization, the model behavior was compared to the behavior of the test subject under consideration. First, the initial vehicle state (position, velocity, acceleration, and heading) was read from data and assigned to the simulated vehicle. Then, in each time step of the simulation, the exact position and heading of the actual vehicle (read from data) was assigned to the simulated vehicle. A steering wheel angle could then be calculated in each time step using the driver model (comparing the actual path to the desired path). In order to evaluate the behavior of the model for a given set of parameter values, a fitness value was calculated as

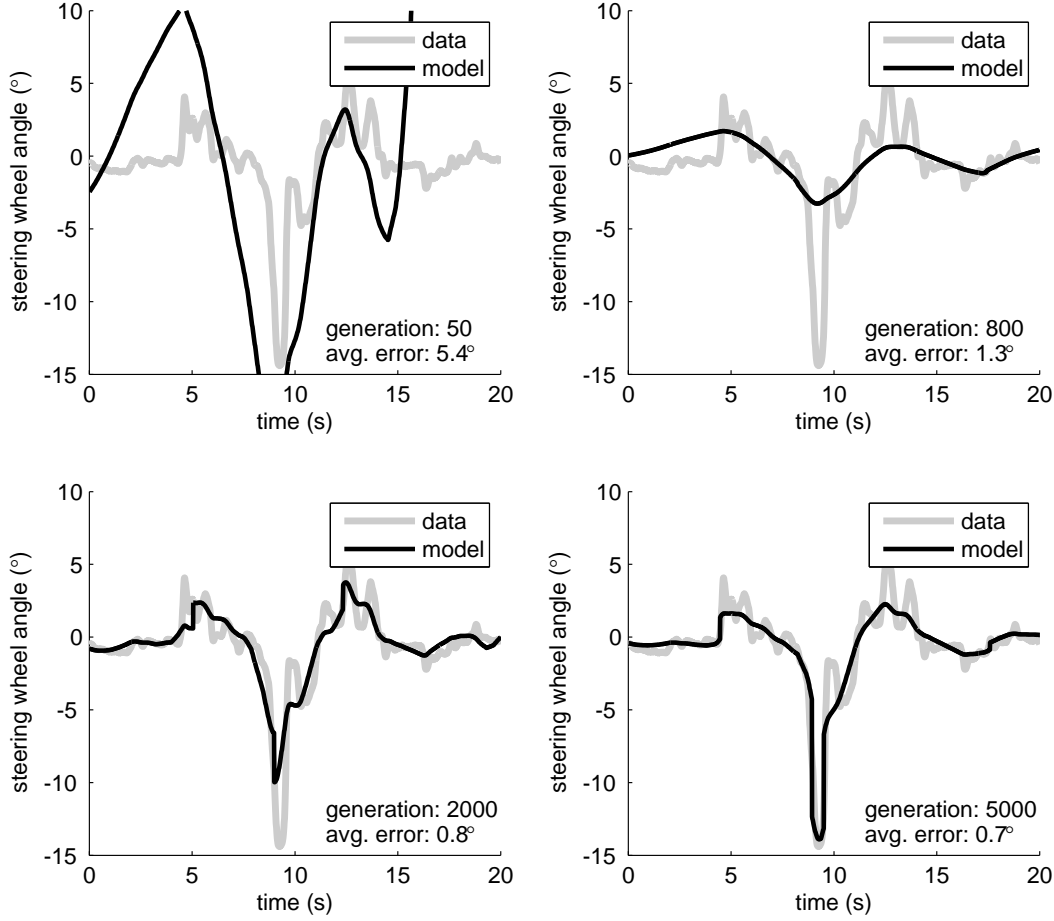


Figure 5.3: An example of driver model tuning. The panels show the steering wheel angle variation for the best individual in generations 50, 800, 2000, and 5000.

the inverse of the average steering error ϵ given by

$$\epsilon = \frac{1}{n} \sum_{j=1}^n |v(j) - u(j)| \quad (5.2)$$

where $v(j)$ is a sample in the steering angle signal obtained from the data, $u(j)$ the corresponding steering angle acquired from the simulation, and n the number of samples in the steering signal. In other words, given a recorded trajectory, the driver model should ideally produce a steering signal equal to the recorded steering signal associated with that trajectory. If the model can accurately capture the steering behavior of the three drivers, it may be

Training						Validation		Test			
1	1.261	8	1.751	15	1.933	22	1.401	1	1.230	1	1.540
2	1.953	9	1.692	16	1.809	23	1.649	2	1.757	2	1.578
3	2.351	10	1.607	17	1.252	24	1.460	3	1.430	3	2.810
4	1.980	11	1.672	18	1.211	25	1.074	4	2.320	4	1.221
5	1.424	12	1.244	19	1.979	26	1.448	5	1.798	5	2.781
6	1.744	13	2.674	20	1.748			6	1.506	6	1.597
7	1.749	14	1.834	21	1.750						
1.679 (0.358)						1.673 (0.381)		1.921 (0.691)			
1.716 (0.423)											

Table 5.2: *The performance of the average driver measured using the average error in steering wheel angle (in degrees) for each test subject. The mean and standard deviation for the training, validation, and test sets are presented in the second row from the bottom. The bottom row shows the mean and standard deviation over all 38 data points.*

useful for representing an average driver. Here, the criterion for an accurate behavior is a maximum error of three degrees¹.

Fig. 5.3 shows four examples of steering wheel angles obtained during a single optimization run (corresponding to the best individual in generations 50, 800, 2000, and 5000). As can be seen in the bottom right panel of that figure, it turned out that the model could in fact rather well reproduce real driver behavior from the scenario under study, obtaining an average error of around 0.7°.

Therefore, one can expect that the model can be used when finding parameters for the average driver (using all data). For the three tuned driver models, parameter values, as well as average steering error measurements, can be found in Table 5.1.

5.3.2 Parameter optimization

In order to find model parameters for the average driver, all 38 data points were used. Of those, 26 points were used for training, 6 points for validation, and 6 points for testing.

In order to calculate the *combined* error based on several steering angle references, Eq. (5.2) was generalized so that ϵ instead is given by

$$\epsilon = \frac{1}{m} \sum_{i=1}^m \left(\frac{1}{n_i} \sum_{j=1}^{n_i} |v_i(j) - u_i(j)| \right) \quad (5.3)$$

¹With a steering gear ratio of 16, a 3° change in steering wheel angle corresponds to a change in *vehicle* steering angle of approximately 0.2°.

where i denotes the test subject, m the number of test subjects, and n_i the number of time steps for test subject i . The resulting driver model parameters are presented in Table 5.1 and the model's performance is presented in Table 5.2.

Discussion

In this thesis, the three driver modeling aspects of design, data collection, and parameter tuning have been described and exemplified. In this chapter, these aspects will be discussed further, with emphasis on driver model development.

6.1 Selecting a suitable model design

The selection of a suitable model depends very much on the application in which it will be used. In Paper I, four different groups of applications were identified as (i) vehicle and infrastructure design, (ii) analysis of naturalistic driving data, (iii) complement to a limited set of driving data, and (iv) reconstruction of accidents. In a scenario involving vehicle testing, the driver model is typically not very important, implying that a simple control theory model normally would be best suited. In applications where the driver plays a central role and where the actions of the driver will be under study, a behavioral or cognitive model (as presented in Chapter 2) would generally be better suited.

In Paper I, it was concluded that there are no straightforward general recommendations for selecting a driver model, even though simple models such as the GHR model (described in Sect. 2.2) have been used successfully in a wide range of applications. It was also concluded that many of the previous driver modeling efforts have resulted in new driver models designed specifically for the application at hand. However, by comparing driver models using computer simulations in the simulation environment described in Chapter 4, it was found that different models are, in fact, often very similar in their control behavior. Furthermore, it was noted that efforts in com-

paring models have been rather limited, leading to the suggestion (Paper I) that, before starting a new driver modeling effort, one should make sure to evaluate *existing* driver models first.

Another aspect of choosing a model concerns the number of parameters within the model. Parameters can be set manually, but this process can be impractical even in models with rather few parameters, particularly in cases where the combined action of the parameters is difficult to overview manually. Therefore, it is often better to tune parameters automatically from driving data, as exemplified by the optimization approach presented in Chapter 5 and in Paper II. Either way, the amount of available data will put restrictions on the number of parameters in the selected model.

6.2 Collecting data in repeated exposures

As just mentioned, in order to tune a driver model, one typically needs a large set of data regarding driver behavior. However, when studying critical situations, such as a head-on collision scenario, it is hard to collect large amounts of data, due to safety and expectancy reasons. Additionally, it is not always so that, for a critical situation, the desired behavioral response is always present. For example, in the lead vehicle braking scenario described in Paper III and in Sect. 3.1, it was found that 52% of all the truck drivers failed to apply sufficient evasive steering. It was also found that 23% of the drivers did not attempt any steering at all. In previous studies, it was also found, by similar quantities, that drivers did not attempt evasive actions [1, 17]. Therefore, when studying the dynamics of such actions, this kind of passive behavior results in loss of data¹.

In the two experiments described in Chapter 3, repeated exposures of an (initially) unexpected scenario were used in order to collect larger amounts of data. In Papers III and IV it was concluded that repeated exposures to a critical event can indeed be used when collecting behavioral data for driver modeling, especially when collecting *steering* behavior, at least in collision avoidance. In Paper III, it was shown that brake reaction times are significantly lower and braking is significantly stronger in an expected (repeated) scenario. Similar results have been found by other authors [9, 18]. However, in Paper IV, steering behavior in the repeated scenario was found to be similar to that observed in the unexpected scenario. Moreover, for a given individual, the steering behavior obtained in the unexpected scenario was (partly) transferred to the repeated scenarios.

¹However, the frequency of passive behavior is a very important aspect when developing a driver model.

In order to further increase the amounts of data collected, the unexpected scenario described in Sect. 3.1 was appended to an unrelated driving simulator experiment. As described in Paper III, it was concluded that this method might be beneficial, but also that it puts increased demand on efforts to control for any undesired effects on behavior due to differences in experimental setup. In that particular case, the test subjects were moved from a summer environment where the main experiment was conducted, to the winter environment where the appended unexpected scenario would occur. By comparing driver behavior with behavior from the original experiment in which a winter setting was used throughout, one could suspect that drivers assumed the road to be more slippery than in the original experiment.

6.3 Validating driver models

As concluded in Paper I, many driver models have not been subjected to validation using real driving data (in particular, FOT data or accident statistics). In many cases, the lack of validation is due to insufficient amounts of data. As stated in Paper I, the process of validation is far from trivial. For instance, even if large amounts of data are collected in a driving simulator, one cannot use the data both for generating and fully validating a driver model, due to potential effects on driver behavior from the experiment setting (as exemplified near the end of the previous section). For proper validation, the behavior of the driver model must be compared to driver behavior data collected, for instance, from FOT studies or accident statistics.

As an illustrative example, here, a driver model [36] has been tuned to data collected in a driving simulator experiment (see Chapters 3–5). A potential problem, however, is suggested by Table 5.1. As can be seen in the table, using very different parameter values the model is capable of representing three different driver steering behaviors. It can thus be suspected that the model is generally very flexible in representing steering behavior, perhaps due to its complexity (number of parameters). A problem with such a flexible model [34], is that its parameters probably do not relate to real driver properties (see also the discussion about cognitive models in Chapter 2 on p. 8). For instance, the preview time parameter could easily be recognized as a driver property, but when looking at the values presented in Table 5.1, one can see that it takes very different values for each subject (yet for the exact same scenario). Therefore, one can suspect that preview time does not, in this case, relate very well to the real driver behavior, nor, unfortunately, does it indicate the preview time used by the real driver. Possible solutions to this problem would be to (i) use general (proven) models of human be-

havior, (ii) use simpler models with minimal parameter redundancy, or (iii) analyze driving data to determine, or at least to narrow, the range of the model parameters.

Another important factor when discussing the validity of a model is the one of **driver types**. In Paper III, it was shown that experienced drivers behaved significantly different compared to inexperienced drivers. In the example of driver model parameter tuning presented here, an *average* driver model was created based on driving data collected from 38 test subjects. Still, after optimization, the driver model does not fully represent any of these drivers. Therefore, it can be argued that one should avoid reducing the behavior of a large population by, for instance, representing the behavior with only a single set of parameters. There are at least two ways to avoid this problem. First, one could use parameter *distributions* instead of single values. For instance, one could tune a mean and standard deviation for each parameter in the model, and then draw values randomly from that distribution. A second solution would be to divide the subjects into groups and then tune the model separately for each group. Preferably, the groups should be based on behavior, so that each group corresponds to a driver type.

The driver model used in Chapter 5 was tuned to one very specific scenario (i.e. a DLC). In that scenario the optimized model behaves roughly as a human driver. However, if the same driver model parameter values would be applied in a different scenario, the driver model would most probably produce a far from realistic steering behavior. In Paper I, the possibility of having different **control modes** [11] was discussed. For instance, the model could switch between different model parameters, or even different models altogether, when exposed to *fundamentally* different situations. Another possible solution, commonly referred to as **adaptation** [38], would be to continuously tune the driver model in real-time by following pre-defined gain-scheduling rules.

Conclusions and further work

7.1 Conclusions

The main conclusion that can be drawn from the results obtained in this thesis is that repeated events can, at least to a certain extent, be used when collecting data for driver modeling. This is important since, for proper parameter tuning and validation of driver models, large amounts of data are required in order to avoid overfitting.

In Paper I it was concluded that driver models have often been developed without any regard to existing models that, in many cases, may have similar performance. Thus, a general recommendation (given in Paper I) is to consider the capabilities of existing models before embarking on a new modeling effort. Furthermore, in Paper I it was also concluded that most driver models lack proper validation against driving data, partly because of the large amounts of data required for such validation, as described above. For full validation, the behavior of a driver model should be tested against sufficiently large sets of data and also, preferably, using FOT data or accident statistics, if available.

As for data collection, by analyzing the results from a truck simulator study, it was concluded in Paper III that a large portion of the drivers (52%) failed to apply sufficient evasive steering in an unexpected lead vehicle braking scenario, leading to a significant loss of steering data something that, in turn, makes it difficult or impossible to tune driver model parameters based on the collected data.

A solution to this problem is to use multiple repetitions of the critical scenario. While not all aspects of driver behavior are likely to be conserved between an unexpected scenario and a repeated exposure, it was found (in Paper IV) that driver *steering* behavior in a collision avoidance scenario is

largely preserved between unexpected and repeated tests, thus making it possible to collect sufficient amounts of data for driver modeling.

However, for any given experiment, one must, of course, determine whether the studied aspects are indeed conserved between unexpected and repeated events, for example by means of statistical tests as used in Papers III and IV.

An example of driver model parameter tuning has been presented in Chapter 5, using the driving simulation environment first presented in Paper II. It was concluded that the model was capable of representing a large variety of driver behaviors. On the other hand, rather than capturing actual driver behavior properties, such as the concept of a *preview time*, the model simply provided the best possible control behavior in a phenomenological way. It was thus hypothesized (see Sect. 6.3) that a simpler, less flexible, model with fewer parameters probably would be better at capturing true driver behavior properties.

7.2 Further work

Before carrying out additional driver modeling efforts, it would be valuable to extend the model comparisons from Paper I, in order to gain deeper knowledge on the behavior of existing driver models. By also comparing how well the models can capture *actual* driver behavior parameters, one could determine which models would be most suited.

Another future topic would be to improve the driver model tuning process by incorporating general driver properties into the fitness measures used during optimization. Some such driver properties are mentioned in Chapter 2, for example the crossover model, sensitivity to looming effects, and relationships between lateral and longitudinal accelerations. By finding as many such properties as possible and including them as constraints during optimization, one could ensure more realistic driver models.

In addition, it would be interesting to study the concept of control modes, and also to investigate how stochastic optimization can be used to capture the transitions between such modes. Such an endeavor should start with further analysis of control modes in real driver behavior and how real drivers switch between such modes.

Finally, an important topic for further work will be to improve the method of repeating critical events in driving simulator experiments. By doing so, one could define general guidelines for how to reduce the effects of expectancy, and also further study which variables are affected by repetitions and which are not. Furthermore, it would be valuable to determine limits on how many

times a given scenario can be repeated for a single test subject without seeing learning effects and loss of concentration.

Bibliography

- [1] L. ADAMS, *Review of the literature on obstacle avoidance maneuvers: Braking versus steering*, tech. rep., University of Michigan, Transportation Research Institute, 1994.
- [2] J. ANDERSON, M. MATESSA, AND C. LEBIERE, *ACT-R: A theory of higher level cognition and its relation to visual attention*, *Human-Computer Interaction*, 12 (1997), pp. 439–462.
- [3] R. BISHOP, *Intelligent Vehicles Technology and Trends*, Artech House, 2005.
- [4] T. BUTZ AND O. VON STRYK, *Optimal control based modeling of vehicle driver properties*, Tech. Rep. 2005-01-0420, SAE International, 2005.
- [5] M. DORIGO AND G. DI CARO, *Ant colony optimization: a new meta-heuristic*, in *Proceedings of the 1999 Congress on Evolutionary Computation*, vol. 2, IEEE, 1999.
- [6] J. ENGSTRÖM, *Understanding Attention Selection in Driving: From Limited Capacity to Adaptive Behavior*, PhD thesis, Chalmers University of Technology, 2011.
- [7] D. GAZIS, R. HERMAN, AND R. ROTHERY, *Nonlinear follow-the-leader models of traffic flow*, *Operations Research*, 9 (1961), pp. 545–567.
- [8] T. GORDON AND N. MAGNUSKI, *Modeling normal driving as a collision avoidance process*, in *Proceedings of 8th International Symposium on Advanced Vehicle Control*, 2006.
- [9] M. GREEN, *"How long does it take to stop?" methodological analysis of driver perception-brake times*, *Transportation human factors*, 2 (2000), pp. 195–216.

-
- [10] J. HOLLAND, *Adaptation in natural and artificial systems*, no. 53, University of Michigan press, 1975.
- [11] E. HOLLNAGEL AND D. D. WOODS, *Joint cognitive systems: Foundations of cognitive systems engineering*, CRC Press / Taylor & Francis, 2005.
- [12] ISO, *Passenger cars – test track for a severe lane-change manoeuvre – part 1: Double lane-change*, 1999.
- [13] R. JURECKI AND T. STAŃCZYK, *Driver model for the analysis of pre-accident situations*, *Vehicle System Dynamics*, 47 (2009), pp. 589–612.
- [14] T. JÜRGENSOHN, *Control theory models of the driver*, in *Modelling Driver Behaviour in Automotive Environments*, P. Cacciabue, ed., Springer, 2007, pp. 277–292.
- [15] J. KENNEDY AND R. EBERHART, *Particle swarm optimization*, in *Proceedings of the 1995 IEEE International Conference on Neural Networks*, vol. 4, IEEE, 1995, pp. 1942–1948.
- [16] S. KHARRAZI AND R. THOMSON, *Analysis of heavy truck accidents with regard to yaw & roll instability using ltccs database*, (2008).
- [17] D. LECHNER AND P. VAN ELSLANDE, *Comportement du conducteur en situation d'accident*, *Ingénieurs de l'automobile*, (1997), pp. 64–70.
- [18] J. LEE, D. MCGEHEE, T. BROWN, AND M. REYES, *Collision warning timing, driver distraction, and driver response to imminent rear-end collisions in a high-fidelity driving simulator*, *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 44 (2002), pp. 314–334.
- [19] Z. LI AND P. MILGRAM, *An empirical investigation of the influence of perception of time-to-collision on gap control in automobile driving*, in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 48, 2004, pp. 2271–2275.
- [20] M. LIN, A. POPOV, AND S. MCWILLIAM, *Sensitivity analysis of driver characteristics in driver-vehicle handling studies*, in *Driver Behaviour and Training*, L. Dorn, ed., Ashgate Publishing Ltd, 2003, pp. 263–276.
- [21] C. MACADAM, *Application of an optimal preview control for simulation of closed-loop automobile driving*, *IEEE Transactions on Systems, Man, and Cybernetics*, 11 (1981), pp. 393–399.

-
- [22] —, *Development of a driver model for near/at-limit vehicle handling*, Final report UMTRI-2001-43, University of Michigan Transportation Research Institute, 2001.
- [23] D. MCRUER, L. HOFMANN, H. JEX, G. MOORE, AND A. PHATAK, *New approaches to human-pilot/vehicle dynamic analysis*, tech. rep., DTIC Document, 1968.
- [24] D. MCRUER AND E. KRENDEL, *The man-machine system concept*, Proceedings of the IRE, 50 (1962), pp. 1117–1123.
- [25] —, *Mathematical models of human pilot behavior*, tech. rep., DTIC Document, 1974.
- [26] W. NAJM, J. SMITH, AND M. YANAGISAWA, *Pre-crash scenario typology for crash avoidance research*, Final report DOT HS 810 767, U.S. Department of Transportation, 2007.
- [27] C. OH, Y. KANG, AND W. KIM, *Assessing the safety benefits of an advanced vehicular technology for protecting pedestrians*, Accident Analysis & Prevention, 40 (2008), pp. 935–942.
- [28] H. PACEJKA, *Tyre and Vehicle Dynamics*, Butterworth-Heinemann, 2002.
- [29] G. PROKOP, *Modeling human vehicle driving by model predictive online optimization*, Vehicle System Dynamics, 35 (2001), pp. 19–53.
- [30] R. RAJAMANI, *Electronic stability control*, Vehicle Dynamics and Control, (2012), pp. 201–240.
- [31] P. RAU, *Drowsy driver detection and warning system for commercial vehicle drivers: field operational test design, data analyses, and progress*, in Proceedings of 19th International Conference on Enhanced Safety of Vehicles, 2005.
- [32] A. REŃSKI, *Identification of driver model parameters*, Int J Occup Saf Ergon, 7 (2001), pp. 79–90.
- [33] M. RICHTER, H. PAPE, D. OTTE, AND D. KRETTEK, *Improvements in passive car safety led to decreased injury severity – a comparison between the 1970s and 1990s*, Injury, 36 (2005), pp. 484–488.
- [34] S. ROBERTS AND H. PASHLER, *How persuasive is a good fit? a comment on theory testing*, Psychological review, 107 (2000), pp. 358–367.

- [35] D. SALVUCCI, *Modeling driver distraction from cognitive tasks*, in Proceedings of the 24th Annual Conference of the Cognitive Science Society, 2002, pp. 792–797.
- [36] R. SHARP, D. CASANOVA, AND P. SYMONDS, *A mathematical model for driver steering control, with design, tuning and performance results*, *Vehicle System Dynamics*, 33 (2000), pp. 289–326.
- [37] K. SMITH AND J. KÄLLHAMMER, *Driver acceptance of false alarms to simulated encroachment*, *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 52 (2010), pp. 466–476.
- [38] M. THOMMYPILLAI, S. EVANGELOU, AND R. SHARP, *Car driving at the limit by adaptive linear optimal preview control*, *Vehicle System Dynamics*, 47 (2009), pp. 1535–1550.
- [39] A. TUSTIN, *The nature of the operator’s response in manual control, and its implications for controller design*, *Journal of the Institution of Electrical Engineers Part IIA: Automatic Regulators and Servo Mechanisms*, 94 (1947), pp. 190–206.
- [40] M. WAHDE, *Biologically Inspired Optimization Methods: An Introduction*, WIT Press, 2008.
- [41] B. WANG, M. ABE, AND Y. KANO, *Influence of driver’s reaction time and gain on driver–vehicle system performance with rear wheel steering control systems: part of a study on vehicle control suitable for the aged driver*, *JSAE review*, 23 (2002), pp. 75–82.
- [42] J. P. WANN AND R. M. WILKIE, *How do we control high speed steering?*, in *Optic Flow and Beyond*, L. M. Vaina, S. A. Beardsley, and S. K. Rushton, eds., Dordrecht: Kluwer Academic Publishers, 2004, pp. 371–389.
- [43] G. S. WATSON, Y. E. PAPELIS, AND O. AHMAD, *Design of simulator scenarios to study effectiveness of electronic stability control systems*, *Transportation Research Record: Journal of the Transportation Research Board*, 1980 (2006), pp. 79–86.
- [44] J. WOODROOFFE, D. BLOWER, T. GORDON, P. GREEN, B. LIU, AND P. SWEATMAN, *Safety benefits of stability control systems for tractor-semitrailers*, (2009).

-
- [45] WORLD HEALTH ORGANIZATION, *Global status report on road safety: Time for action*, 2009.
- [46] M. YAMAKADO AND M. ABE, *An experimentally confirmed driver longitudinal acceleration control model combined with vehicle lateral motion*, *Vehicle System Dynamics*, 46 (2008), pp. 129–149.
- [47] H. YANG AND H. PENG, *Development of an errorable car-following driver model*, *Vehicle System Dynamics*, 48 (2010), pp. 751–773.
- [48] Y. ZEYADA, E. EL-BEHEIRY, M. EL-ARABI, AND D. KARNOPP, *Driver modeling using fuzzy logic controls for human-in-the-loop vehicle simulations*, in *Current advances in mechanical design and production VII: proceedings of the Seventh Cairo University International MDP Conference*, 2000, pp. 85–94.
- [49] S. ZHANG, G. WU, AND S. ZHENG, *Speed following driver model based on self-adaptive chaotic genetic PID and preview control*, *ICIC Express Letters*, 5 (2011), pp. 4041–4046.

