Identification and modeling of behavioral changes in longitudinal driving through vehicle-based signals

Mairi Panagopoulou

Faculty of Civil Engineering and Geosiences

TUDelft
Delft University of Technology

TNO innovation for life

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Mairi Panagopoulou

Transport and Planning
Department of Civil Engineering and Geosciences, Delft University of Technology

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Author	M. Panagopoulou, Msc
Graduation committee	Prof. dr. ir. B. van Arem
	Dr. R.G. Hoogendoorn
	Ir. P.B.L. Wiggenraad
	Ir. S.T.H Jansen
	Dr. M. van Noort
	Dr. R. Happee
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Cover photo: Dmitri Kalinin, Moscow circle highway at night, http://www.flickr.com
Cover illustration: Angelos Bousias

"And suddenly I realized that I was no longer driving the car consciously. I was driving it by a kind of instinct, only I was in a different dimension."

Ayrton Senna

Abstract

Vehicles are an integral part of everyday life. Since drivers depend on these transport means to perform their activities, it is important to investigate how they behave inside the vehicles in order to facilitate their task and avoid any undesired consequences (e.g. congestion, accidents). Different components of the driving environment have an influence on the driving behavior and the main objective of this thesis is to identify the points where the driving behavior changes due to these driving factors. From the driving conditions the traffic flow and its composition, the road geometry, the traffic signs and the traffic lights are selected and are analyzed through the use of vehicle-based systems. The actual situation that occurs in the road is determined from cameras mounted on the vehicle. For the identification of the driving behavior a simple car-following model is used, the Helly model. The first part of this study consists of the estimation of the parameters of the car-following model, while the second part consists of the identification of the points where these parameters change due to the exogenous driving factors. The estimation of the parameters is achieved through an optimization procedure which uses a moving estimation window and searches for constant sets of parameters in that time window. The estimation model performs well only under car-following situations. When the car-following task is achieved, the change of lanes, the traffic lights and the changes in the traffic conditions are found to have an influence in the parameters of the Helly model. In contrast, the composition of traffic and the existence of on-ramps and off-ramps in the road do not influence the driving behavior. The proposed system captures the intra-heterogeneity in driver's behavior when performing the same action under the same circumstances. A future real-time application which would identify the driving behavior and the action points would be a valuable tool for the traffic management operations because the traffic flow phenomena could be recognized and predicted directly and more accurately. Another useful application could be found in traffic safety operations where the automated vehicles would be able to provide the right information in the appropriate phase.

Preface

"Sometimes I think I know some of the reasons why I do the things the way I do in the car. And sometimes I think I don't know why. There are some moments that seem to be only the natural instinct that is in me. Whether I have been born with it or whether this feeling has grown in me more than other people, I don't know. But it is inside me and it takes over with a great amount of space and intensity." The words of people like Ayrton Senna who drove professionally, make us think to what extent is the driving task connected with the subconsciousness and whether the experienced people have time to think before reacting in different environmental conditions. That motivated me to come up with a system that can identify the behavior of the driver under different situations. My main objectives were to determine the main causes for changes in the driving style, the behavior of the driver under similar conditions and the reproduction of the driving behavior with a model as close to reality as possible.

This thesis marks the end of my master's graduation project in Civil Engineering, track Transport and Planning, at the Delft University of Technology. The research leading to this master thesis was conducted at TNO mobility in Delft and Eindhoven. For that reason I would like to thank the organizations TNO and TU Delft that made the work presented in this master thesis possible.

I first of all want to thank the people in my graduation committee who contributed to this thesis. Professor Bart van Arem for giving me the opportunity to perform my thesis research within this project. My daily supervisor Raymond Hoogendoorn for his continuous motivation to follow the direction that I would enjoy more and for his support on my ideas and thoughts about the project. My weekly supervisor from TNO, Sven Jansen, for his effort to make me think of the practical contribution of my thesis, for his continuous advice and his restless explanations whenever I faced difficulty in understanding some concepts. In addition, I would also like to thank Martijn van Noort for his useful and always well-supported comments of which this thesis certainly benefited. Also, I would like to thank Paul Wiggenraad for helping me with the administrative paperwork that I had to prepare and Riender Happee for the critical questions he addressed to me.

Furthermore, I would like to thank the secretaries of TNO, Mariska and Christine, for offering their help whenever I needed it and the secretaries of the Transport and Planning department for arranging my meetings. I also want to express my gratitude to all the people in TNO who had driven a lot of hours to collect the data that I needed for my experiments.

I especially want to acknowledge my fiance, Angelos Bousias for offering his programming skills whenever I asked, for simplifying my code, for understanding my research ideas and advising me and most of all for being there and supporting me in my decisions. Without him this thesis would not have existed at all.

Finally, to my family for their mental and economical support, a big thank you! And to all the other people who contributed in one way or another to this dissertation and I forgot to mention, Thank you as well!

Yours sincerely,

Mary Panagopoulou
Delft, April 2014

Executive Summary

Driving behavior constitutes an endless subject for research. What makes the driving behavior so complex are the different components that have to be investigated and the interaction between them. Thus, the research scope changes under the interest of the stakeholder to research from a psychological point of view, a transportation point of view, a mechanical side etc. In this thesis, the behavior of the driver is identified from a transportation point of view. This means that the research is focused on the movement of the car in the road (acceleration, deceleration) and the main objective is to identify the driving factors that influence the driver to change his driving style and as consequence the movement of the car. The identification of the driving behavior would permit the control and prevention (if necessary) of the vehicle's movements.

Different types of data can be used to identify the behavior of the driver and the selection of the appropriate type is related to the research scope. In this thesis, the identification is made through vehicle-based signals since they offer a more accurate identification of the driving task. These signals enable the identification of the driver's longitudinal acceleration over time and the comparison of the calculated item with the actual acceleration which is also taken from the vehicle's system. The data collection procedure is only carried out in highways, with two different drivers and with the use of two passenger cars. The data that are used for the identification are the longitudinal velocity and the longitudinal acceleration, the steering, the relative velocity and the relative distance.

For the identification of the vehicle's acceleration over time, a car-following model is used, the Helly model. The parameters of the Helly model are identified by using an optimization tool which minimizes the difference between the calculated and the observed acceleration. These parameters are the sensitivity of the relative speed, the sensitivity of the speed differences with the lead vehicle, the minimum stopping distance and the minimum time headway. For the identification, a moving time window of 3 minutes is used since the driving style, described by the parameters, changes over time. The points where the accelerations differ considerably are examined separately to investigate whether the car-following model does not work or the driving style has changed and a new estimation is needed. If the latter is the case, these points are recognized as action points and the optimization is repeated until the new driving style is defined.

The results of the model are extensively analyzed and compared with the camera data that are collected in the field in order to further investigate the relationship between the action points and the driving environment. It is verified that the Helly model can not give reliable results when there is not an actual car-following situation (relative distance higher than 100 meters). Furthermore, the Helly model cannot produce accurate results when the driver continuously changes lanes or when the lead vehicle presents a large variation in its movement. However, the model is able to demonstrate that the traffic lights, the change of lanes and the change of traffic conditions are action points where the driving style changes. A further investigation is made to identify the consequences of the action

points in different data sets and to analyze the appearance of the consequences whenever the same conditions apply. It is found that a constant set of parameters can be applied for each driver under the simple car-following task, so the heterogeneity within the same driver is captured. In addition, a list is created with all the conditions under which the driving style was expected to change, but the driver is found to adapt in the new situation without a change in his style.

The results of this project are very useful for traffic management operations and for the evaluation and development of safety systems. Since the driving behavior is known, suggestions can be provided to the driver in order to avoid traffic, to reduce his travel time, to avoid an accident, etc. The proposed methodology identifies the driving behavior from vehicle-based signals. The model can be adapted in many existing systems and also creates the base for driving identification in real-time. A different estimation model is recommended for a real-time application which will enable the driving identification under a larger variety of conditions and not only in car-following situations. Finally, future research should examine a larger variety of driving conditions and their influence on the driving behavior and compare the results from vehicle-based signals with results from other types of data that already exist in the literature (e.g. behavioral measurements).

Contents

Chapter 1

Introduction

1.1 Context

The last decades traffic flow modes are used in order to describe, predict and control the traffic conditions in a road network. These systems are based on analytical modeling and simulation. Traffic flow models are part of a long history of mathematical modeling of physical and other systems. Scientists and engineers use these models as simplified representations of real-world systems. By doing simulations based on these models, the performance of roads or traffic networks can be assessed. This includes answering questions about the presence and duration of congestion, travel times and delays and the ex-ante evaluation of traffic management measures.

The behavior of the driver is a very important factor in traffic operations. Although some models (i.e. microscopic models) take the behavior of the driver into account, they do not sufficiently incorporate the changes in driving behavior and the differences between drivers. Different studies [4, 50] have been made which show that the driver's behavior has an important effect on traffic operations. However, a driver is also affected by the traffic operations and reacts on them according to his own sensors and his own decision process. The main goal of this report is to identify the behavior of the driver, to determine the points where this behavior changes and to investigate the conditions that may be responsible for a change in driving style. In order to model driver's behavior, vehicle-based signals and data from on-vehicle camera are used which are collected by TNO Mobility[1].

Through the vehicle-based signals and the use of camera data, the behavioral adaptation of the driver is modeled. With the proposed model it will possible to identify the impact of the existing traffic flow, the road geometry, the traffic signs and traffic lights on the driver's behavior. A useful application of this project is in traffic flow operations as the driver can receive suggestions on how to avoid traffic or reduce his travel time. The driver will always have an important role in vehicle dynamics, not only during manual control but also during supervisory control of an automatic system. Thus, another useful

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[1]http://www.tno.nl

application of the findings of this dissertation could be in intelligent vehicle systems as the information that is provided to the driver can be tailored to the specific situation if the expected behavior of the driver is already known.

In this thesis, first the different components of the driving environment are analyzed in order to investigate whether they influence the driver's behavior. Then the vehicle-based signals are used in order to identify the behavior of the driver (estimation of the parameters of a car-following model). By using the estimated behavior, the action points could be identified and correlated with changes in the driving environment.

1.2   Research scope

In order to investigate driver's behavior from vehicle-based signals, only freeways will be considered and not secondary road networks. Traffic operations take place usually in highways where there are available systems (loops, cameras) for measuring the effects in the networks. The vehicle-based signals that are used in this study are selected after driving on dutch highways (A2, A67, A270). The driving environment on secondary roads totally differs from the conditions on a highway and the driver is affected from a variety of factors that need different analysis in order to investigate his behavior. Thus, the following research is focused on highways and the transition from the highways to the secondary roads is also considered as a change in the driving conditions but without further analysis on the secondary road network.

The vehicle-based signals that are used offer information only about the lead and the ego vehicle in the same lane. The main reason for this choice is the availability of those data. The second reason is the focus of this research on the methodology and on whether the identification can be performed with vehicle-based signals. Thus, only the interaction with the lead vehicle is examined in this case as it is simpler and it would be easier to assess the methodology from the results. However, in the future the interaction with more vehicles is recommended. For the assessment of the driving behavior due to the traffic state or the traffic composition, the existence of the vehicles in the other lanes is taken under consideration from the camera data.

1.3   Research questions

The objective of this graduation project is to identify the behavior of the driver in a baseline scenario, in which the driver does not have any information provided by roadside and in-vehicle systems. Only the factors of the driving environment affect the driver in his decisions and as a consequence in his actions. The driving scheme consists of the complex vehicle-driver-environment. The influence comes from the environment to the driver
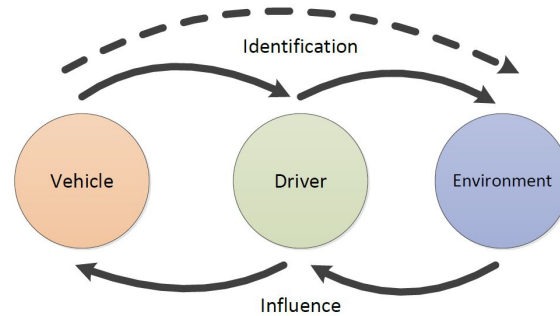
Figure 1.1: The system that is used.

and as a result to the vehicle, while the identification uses the opposite direction, from the vehicle to the driver and then to the environment (Figure 1.1). The dashed arrow describes the automated vehicles that are able to detect the environmental conditions, but in this thesis only the simple case without intelligent systems is considered.

With this theoretical framework of the driving behavior in the baseline scenario, it is possible to identify the driver's behavior by determining the parameters that have to be applied in a car-following model. The second part identifies the points where these parameters change and the consequences that lead to those changes (factors of the driving environment). By obtaining this knowledge, a better formulation of traffic flow models would be feasible. Furthermore, the intra driver heterogeneity of the driver is an important problem in most traffic models, hence it is very challenging to identify a unified behavior of the driver under specific circumstances.

The present thesis is scientifically relevant and challenging in comparison with previous studies [51, 78], since the identification of the driving behavior is based on vehicle signals. This offers more system efficiency since vehicle-based signals are more accurate than other types of data (GPS, helicopter, simulation data). Another challenge is the creation of a method which uses these data for identification since no previous studies have dealt with them. A step beyond the existing researches is the identification of action points and their connection with factors of the driving environment.

Six research questions are formulated in order to settle the requirements of the project. The formulation of these research questions is derived by a combination of the studied literature and the objectives of this thesis. The method that is used to formulate the research questions is the "split research model" method: first the objectives of the project and the steps to reach those objectives are developed and then the model is split into recognizable parts with a question from each part leading to the next part. The first three questions are answered from the literature study and the others are answered from the research that is conducted.

1. What are the components of the driving environment that influence the behavior of the driver and which of them are more important in a car-following scenario?

From the state-of-the-art review it follows that the different components of the (outside) driving environment which contribute to its complexity and influence the driver's behavior in highways are the traffic lights and the traffic signs, the possible static or dynamic obstacles (trees, people, animals, rocks), the road and infrastructure characteristics, the weather conditions and the traffic flow in the network. In this sense, from literature it follows that the existing traffic flow in the network (congestion) is the most important parameter. Also, the influence of the curves of the road on the driver and the traffic lights and signs are analyzed in this project, since they have been observed from the available data. The dynamic and static obstacles are rarely observed in highways and in case they are directed to appear in the road the recorded data are not accurate anymore since the "surprise" characteristic of the obstacles is lost. The inattention of the driver due to exogenous (traffic sings, mobile phone) or endogenous (drowsiness) factors is a very important parameter that has to be modeled. However, the difficulty and the complexity of this component does not permit this identification. The weather conditions have also important effect in driving behavior, but they are not included in the proposed framework due to the complexity of the system.

2. What data can be used in order to identify the driver's behavior?

Different types of data can be used for the identification depending on the interest of the research and the availability of the data. That data can be: behavioral measurements, vehicle-based signals, interviews, GPS data, etc. In this project, two types of data are used in order to identify the driver's behavior, the vehicle-based signals and the camera data, since they offer more accurate identification results. The vehicle-based signals that have been used are the velocity of the vehicle, the longitudinal acceleration, the steering and the relative speed and distance to the lead vehicle. The camera data are used in order to relate the behavior of the driver (parameters in the car-following model) with the driving environment (action points).

3. Which car-following models can be used in order to estimate the driver's behavior?

There are a lot of different models that could be used in the determination of the driver's behavior. From those, the stimulus-response models were chosen and specifically the Intelligent Driver Model (IDM) [73] and the Helly model [23] because they are much simpler than other models, they are already used in many existing traffic flow models (e.g. in the ITS modeller of TNO [70]) and they can provide a good fit in long driving data.

4. How can the parameters of the car-following models be estimated?

The parameters of the car-following models can be estimated through a derivation of

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a statistical parameter estimation approach. An optimization method to estimate the parameters of the car-following model is used which minimizes the difference between a calculated and an observed signal. The continuous changes in the driving environment require a time-variant estimation approach and for that reason the optimization is performed with a moving estimation window. Two different optimization methods are tested in order to compare the results and the computation times and propose the best alternative. A nice property of this optimization approach is that it can be easily repeated with different choices or values depending on the interest of the user (the approach is not restricted to the choices made in this research). For example, the user can choose between the different optimization methods based on computational times or can make a choice on the moving estimation window or choose the minimum time period for a driving style to be applied on the data.

5. How can the actions points (the threshold in which the parameters of the models change) be estimated?

The actions points can be estimated from the outcome of the parameter estimation approach. The approach described above determines a constant set of parameters for the whole moving time window. The points where this constant set of parameters fails to describe the observed signal can be recognized as actions points. The verification of those thresholds as action points is made if a new set of parameters can be applied from these points onwards. Thus, the initial constant set of parameters can be replaced by a number of different sets of parameters depending on the number of action points that are found. In this way, the parameter values are not continuous in each moving time window, but they change gradually every time an action point is crossed (step-wise changes).

6. To what extend can the action points be related to changes in the driving environment?

The actions points can be related to changes in the driving environment through close observation of the camera data and visualization of the outcome of the parameter estimation method. Hence, from these observations, the conditions that are responsible for a change in the driving style are reported. Furthermore, the driving factors that were initially expected to influence the driving behavior but they are not found to have any relationship with a change in the driving style are also noted.

1.4   Research relevance

This master's thesis has both scientific and societal relevance. The objective of this project is the identification of the substantial adaptation effects in longitudinal behavior. From a scientific point of view, a new methodology for this identification is developed. An instrumented vehicle is used which can collect information about its movement as well as for the

movement of the other vehicles which travel close to it. Hence, the opportunity to analyze real vehicle-based signals is exploited and different driving conditions are analyzed.

After the parameter estimation, the action points are determined. This results in different sets of parameters every time a threshold is crossed. The action points present a great difference to the existing systems since they imply that the behavior of the driver is not constant but varies with the changes in the driving environment. The camera data permits a connection of the action points with the changes in the environment. The above novelty would affect the future traffic flow models since the correct parameters of the car-following models would be used depending on the circumstances that will occur each moment.

Based on the action points and the driving conditions, the choices (optimization method, accuracy levels) that have to be selected for a real-time application are described, setting the base for a future real-time application. This opportunity offers new possibilities in the scientific research since the traffic flow phenomena can be studied directly and more accurately.

From a societal and practical point of view, this project aims at two majors results. First of all, an improvement in traffic flow operation systems is expected, since the behavior of the driver would be known and better control over the vehicle can be taken through dynamic traffic management applications and in-vehicle systems (informative systems, driver adaptive support systems, etc). For example, the dynamic traffic signs or the traffic lights can be adjusted so that no congestion occurs if the behavior (acceleration) of the driver is known or in case traffic occurs suggestions can be made to resolve it faster. Also, with the assistance of in-vehicle informative systems, it would be known when the advice has to be given and what type of advice is necessary in order to reduce or avoid congestion (e.g. speed reduction, change of lane, etc.). Finally, a substantial effect on safety operations is expected to reduce casualties, economical and medical costs, loss of production capabilities, material and immaterial costs.

1.5 Outline

In this chapter an introduction on this thesis is presented. First the necessity for the research is explained by addressing the problem, mentioning the gaps in the existing systems and demonstrating the difference that this research would make. Then, the main objective is stated and six research questions are formulated to reveal that goal. The scientific relevance of the thesis is pointed out by the novelties of the proposed research and the societal relevance is expected from the use of the research findings.

This dissertation consists of four parts. The first part includes a theoretical analysis of driving behavior and the factors which influence it, the driving conditions, the car-
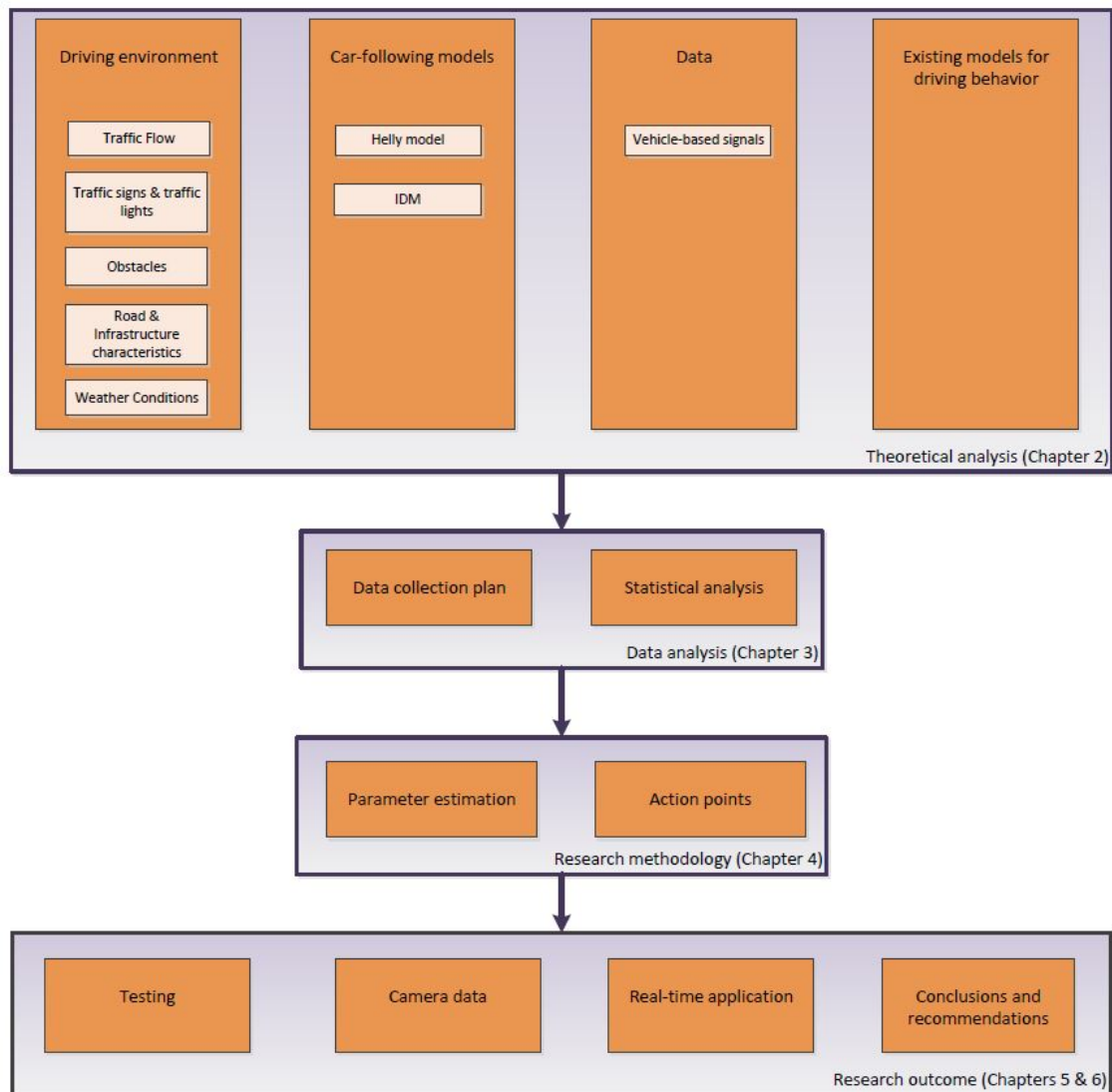
Figure 1.2: Overview of the thesis report.

following models and the existing methods of driving behavior identification (Chapter 2). The second part includes the data collection method and analysis of the vehicle-based signals to ensure that their quality is sufficient for a further research (Chapter 3). The third part includes the methodology for the driving behavior identification and the determination of the action points (Chapter 4). The fourth and last part includes testing of the system with different data sets, the correlation with the camera data and its outcome, the proposals for a real-time application and the overall conclusions and recommendations (Chapters 5 and 6).

Chapter 2

State-Of-The-Art

In this chapter four different topics are discussed. The analysis is based on literature review of existing studies. The four topics are the driving factors and their relationship to the driving environment, the signals that can be used for the identification of the driving behavior, the car-following models and the existing methods for identifying the driver's behavior. The discussion over the driving factors covers all the possible conditions that could influence the driver. The signals that are collected directly from the vehicle are more extensively analyzed since they are used in the current thesis. The discussion is mostly focused on how the existing studies use vehicle-based signals for identifying the driving behavior. However, all the other signals that can be used for the driving identification are mentioned. Except from the use of car-following models, other procedures can be adopted to describe the behavior of the driver from the received data, for example by using Bayesian networks [1]. In this chapter, the car-following models are presented since the parameter estimation of a car-following model is the selected approach for this thesis. The same applies to the methods that can be used to identify the driving behavior which can vary from statistical approaches to artificial intelligence methods.

2.1 The driving environment and its relation to driving behavior

The driving task is a complex task. Drivers have to pay attention to other vehicles, especially more vulnerable road users. Furthermore, the driving task demands are determined by a plethora of interacting elements. There are environmental factors such as visibility, road alignment, road marking, road signs and signals, road surfaces and curve radii, camber angles and so on [19]. Hence, drivers have to observe the road and infrastructure characteristics, the weather conditions, the traffic lights and the traffic signs, unexpected obstacles (humans, animals, rocks, trees, construction signs) and the existing traffic flow [14, 32]. In addition, drivers are influenced from in-vehicle factors (other passengers, radio, in-vehicle systems) and their behavior is influenced from their actions (eating, putting on make-up), their own biological system (drowsiness) or their personal characteristics (age,

experience).

The first factors that have to be examined with regard to their contribution to the driver's behavior are the road and infrastructure characteristics. Richter et al. [60] introduced the road curvature change rate as an independent variable, which served as a criterion of objective road difficulty. They found that psycho-physiological variables (heart rate, blink rate, skin conductance response) and speed varied as a function of the curvature change rate of the road segments, indicating that driving performance significantly deteriorated and visual demand significantly increased as curve radius decreased. Steyvers and De Waard [66] compared continuous and dashed edge lines with two control roads without lines or with only a dashed line on the road axis. Subjectively rated effort was higher for the unlined control road than for the three other roads. It was concluded that edge-lines may provide a simple and effective way of inducing a more favorable lateral position on rural roads without having negative effects on mental workload. Moreover, the number of lanes and the type of road may have an effect on driver's behavior but no related studies have been found to support that statement. The condition of the pavement surface may also have a significant effect in the driver's behavior, but freeways are usually kept in specific levels of PSI (Pavement Surface Index).

Although the effect of pavement surface in freeways does not have a considerable effect on driver's behavior, there is a significant effect if the pavement is wet and slippery. Weather conditions affect driver's behavior, roadway safety, and roadway mobility. According to Goodwin [21], during inclement weather - particularly snowy and icy conditions - drivers increase headway (or spacing between vehicles), decrease acceleration rates, and reduce speeds. Specifically, speed reductions under inclement conditions ranged from 10% to 25% in rainy, wet pavement conditions and from 30% to 40% with snowfall and snowy/slushy pavement. Hoogendoorn [24] corroborates that emergency situations, adverse weather conditions and freeway incidents indeed lead to substantial adaptation effects in longitudinal driving behavior. It was found that in case of fog, drivers significantly reduce their speed along with a reduction in acceleration and an increase in the distance headway. Adverse weather conditions have also found to be related to increases in relative speeds due to increases in the spacing between vehicles. However, for all these adverse conditions a large degree of driver heterogeneity was established.

The traffic signs and the traffic lights are developed in order to control the behavior of the drivers. Summala and Heitamaki [68] tested drivers' reaction in three types of signs for reducing speed (Danger, Children and Speed Limit 30 km/h) and found that drivers responded to them by releasing the accelerator, but they responded more strongly to the more significant signs. A study [29] in the behavior of the driver from dynamic speed limits revealed a substantial change in driving behavior, in particular in the lane distribution, lane change and merging behavior, resulting in a considerable reduction of the freeway capacity. Furthermore, not only the type of the traffic signs influences the drivers but the different characteristics of the drivers are related with different behavior to traffic

signs.

The driver is influenced by the visual environment and reacts sometimes unexpectedly and other times predictably. The reaction of the driver due to obstacles (pedestrians, rocks, animals, incident in-front) is difficult to be analyzed since the obstacles are usually unpredictable. The obstacles are very rare in freeways and since the sudden and unexpected interference in driver's visual environment is the main attribute to his reaction, it is almost not possible to simulate such conditions.

Both the traffic signs and the obstacles may cause driver distraction. Other in-vehicle factors (navigator systems, other passengers, mobile phone) may distract the driver as well. Thus, distraction is an important factor when modeling driver's behavior and has to be parameterized. The distraction of the driver was tested through the use of mobile phones in the car. The effects of three types of cell phones (hand held, hands free with an external speaker and personal hands free) on total subjective workload and intelligibility were measured. In this experiment, the drivers rated all components of workload for each type of cell phone to be significantly higher than for a control condition in which no cell phone was used. It was also concluded that hands free cell phone would interfere less with the cognitive demands of driving [45]. Also, the distraction of the driver starts decreasing when the same source of distraction (e.g. texting) is repeated every day [12].

The studies on telephone devices clearly demonstrate the effect of distraction on drivers. Another research [54] showed that the content of the conversation was far more important for driver distraction than the type of telephone. The more difficult and complex the conversation, the greater the possible negative effect on increment in workload. Moreover, voice or display information systems have an effect on driver's object visual field [36]. Although the in-vehicle devices are not used in this project, the findings are important in order to understand the behavior of the driver when he gets distracted from something he sees (e.g. an animal in the road), since the simulation of distraction due to unexpected obstacles in the driving environment is difficult. Even if a driving simulator is used, the results would not be as objective as in real-driving due to driver's anticipation of the obstacle and the awareness that it is not an real situation.

Distraction is strongly related to the characteristics of the drivers [18]. Men are distracted from the outside environment (Figure 2.1). The distraction of the outside-the-car driving factors (road rage, other vehicles) is stronger than the effect of in-vehicle systems (mobile, smartphone, radio). On the other hand, the effect of factors of the outside driving environment is very limited to women (Figure 2.2), but they are highly distracted by in-vehicle factors (other passengers, kids, navigators, radio) and by their own actions (eating, putting make-up). From the above, it is recommended to test the distraction of the drivers (and as a result the behavior of the drivers) separately for the two genders. It also sets a motive in order to investigate the effect of driver's heterogeneity in driving behavior based on vehicle-based signals.
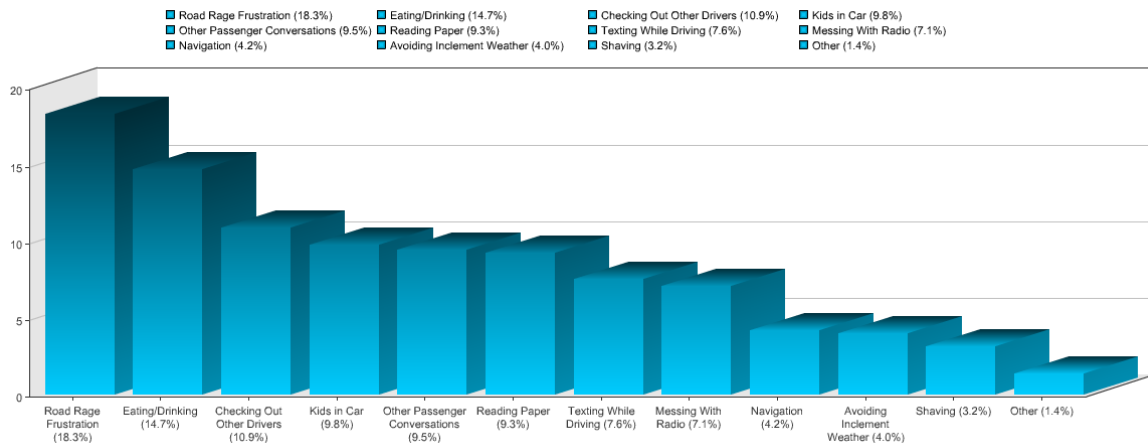
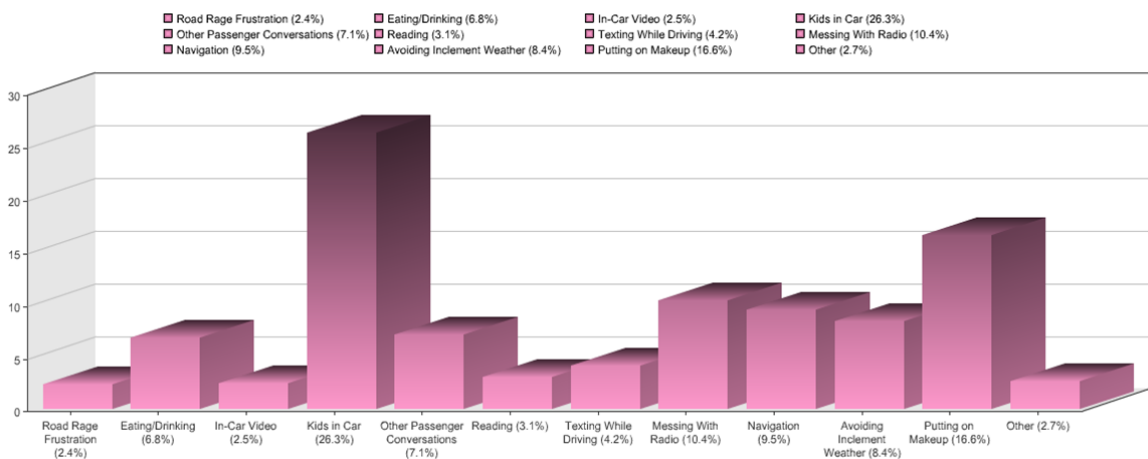Figure 2.1: Sources of distraction of men while driving [18].

Figure 2.2: Sources of distraction of women while driving [18].

The driving environment has been found to have an effect on the driver's mental workload and situation awareness. Situation awareness is often used to describe how much an operator is aware of what is going on around him or her. It is divided into three phases; the perception and integration of situational information into a holistic image and the prediction of future states [17]. Gopher and Braune [22] suggested that the workload construct is conceived to explain the inability of human operators to cope with the requirements of a task, and that workload measurement is an attempt to characterize performance of the task relative to the operator's capability. Mental workload can be expressed by the specification of the amount of information processing capacity that is used for task performance [10]. Verwey [81] suggested that the road situation is a major determinant of visual and mental workload of the driver. The drivers' mental workload is influenced by the characteristics of the driver, the vehicle and the surrounding environment [82]. Wu [77] found

that driver's workload is especially affected by age differences of drivers. Regarding the characteristics of the driver, a study on the effects of mental workload on visual search, discrimination and decision in real traffic conditions showed that the increased workload produce endogenous distraction and spatial gaze concentration, affecting the capacity to process visual stimuli [58].

In an attempt to estimate the mental workload, it was found that increment of mental workload was a function of traffic density, average speed, and uncertainty (estimated by the number of brake depressions) [83]. Following this result, it was suggested that driving workload has two components, a steady-state load dictated by road conditions, speed, and traffic density and a transient load determined by the degree of uncertainty in the driving situation [84].

Much research has been performed on the effect of human behavior from traffic flow operations. Many researchers have tried to investigate how drivers react in different driving situations (congestion, free flow). Studies suggest that human behavior is a contributor to congestion by causing shockwaves through the disturbance of traffic flow and by facilitating the spreading of shockwaves in upstream direction [67]. The main reason behind this is the reaction of the drivers when they observe the congestion in front of them in order to avoid the collision with their lead vehicle. Horrey and Simons [30] examined the impact of mental workload on safety distances that drivers keep when engaged in a tactical control task (passing other vehicles). The results show that although drivers increase their headway adaptively when engaged in steady-state car following, they do not adapt their behavior to accommodate mental workload when performing tactical control maneuvers and implicate the difference between steady-state and tactical control driving contexts.

Other studies showed that Heavy Vehicles (HV) affect driver's mental workload and his driving behavior. An increase in heavy traffic makes merging into and exiting from traffic more mentally demanding and decreases safety margins [15]. Driver's following behavior is also affected by the type of the leading vehicle (drivers follow closer behind trucks/vans than passenger cars) and they are consistent in the choice of their headway [8]. Another reason for this is that drivers in nearly congested traffic tend to change lanes more often under the assumption that the other lane is progressing at a faster pace. Also, research in psychology suggests that people in parallel queuing processes tend to judge their speed by assessing their progress relative to those in the other queue [59]. A possible solution to these negative effects from the driver's behavior has been tried to be achieved through the use of intelligent in-vehicle systems that inform the drivers of the actions that they should take.

The factors that are related to the driving behavior are presented in Table 2.1. The consequences of those factors on the vehicle and the driver are described there. The most common consequences are a speed reduction, the lane changing and the distraction of

Table 2.1: Factors affecting the driving behavior and their consequences.

Factors of driving environment		Consequences
Weather conditions	Rain	Slippery, wet pavement, bad visibility, speed reduction
	Fog	Bad visibility, speed reduction
	Snow	Slippery, wet pavement, bad visibility, speed reduction
	Wind	Speed reduction
	Sun	Bad visibility, speed reduction
Road characteristics	Road markings	Confusion
	Lane separators	Speed increase, speed reduction
Infrastructure characteristics	Curves	Speed reduction
Stationary obstacles	Trees	Distraction, speed reduction, brake down, lane changing
	Rocks	Distraction, speed reduction, brake down, lane changing
	Construction signs	Distraction, speed reduction, lane changing
Dynamic obstacles	Pedestrians	Distraction, speed reduction, brake down, lane changing
	Cyclists	Distraction, speed reduction, brake down, lane changing
	Animals	Distraction, speed reduction, brake down, lane changing
Operation signs	Static signs	Distraction
	Dynamic signs	Distraction
	Traffic lights	Distraction
Traffic flow	Congestion	Speed reduction, lane changing, speed increase, confusion
	Heavy traffic	Speed reduction, lane changing, confusion
In-vehicle factors		
Navigator systems		Distraction, confusion
Passengers		Distraction, confusion
Radio		Distraction, confusion
Mobile phone		Distraction, confusion
In-vehicle systems		Distraction, confusion
Factors related to the driver		
Drowsiness		Distraction, speed reduction
Tiredness		Speed reduction
Driver's actions	Eating	Distraction, confusion
	Putting make-up	Distraction, confusion
Experience		Speed reduction, speed increase
Age		Speed reduction, speed increase, lane changing
Driving style		Speed reduction, speed increase, lane changing

the driver. In the present study, the speed and lane changes due to the other vehicles in the network, the infrastructure characteristics and the traffic signs and traffic lights are examined and not the distraction of the driver (too complicated and large topic to be included in the master's thesis) or the in-vehicle factors (the project is focused in simple, normal driving).

2.2   Signals for identifying the behavioral adaptation of the driver

A lot of different methods can be used in order to identify the behavioral adaptation of the driver. It has to be noticed that the determinants of cognitive processes differ from the driving behavior. The determinants of cognitive processes include all the actions,

thoughts, views of the driver, while driving behavior is the final decision of the driver and as a consequence the vehicle's behavior. Thus, there are different ways to identify the determinants of cognitive processes (driver-vehicle system) and other ways to observe the vehicle's behavior (vehicle-environment system). For the driving (vehicle) behavior GPS systems, cameras, loops, video analysis, vehicle-based signals, car simulators can be used. From the other side, for the determinants of cognitive processes vehicle-based signals and car simulators can also be used, as well as camera data, behavioral measurements, questionnaires/interviews and simple observations.

Behavioral data can be collected from instrumented vehicles which are equipped with various sensors and driving recorder systems in order to detect the vehicle driving status and to measure the driver's operations. Velocity can be measured using a speed pulse signal, and acceleration can be detected by a G-sensor. The relative distance and relative speed to the leading and following vehicles can be recorded by laser radar units or microwave radar in the front and rear bumpers. Laser sensor is widely available and inexpensive, but very sensitive to poor weather and road conditions (blocked by fog and dirt in the air) [42]. Other signals that can be collected from an instrumented vehicle are: the angular velocity by gyro sensor, the geographical position by D-GPS sensor, the application of gas and brake pedals by potentiometers, the position of driver's right foot by laser sensors, the steering wheel angle by encoder and visual images (forward and rear scenes, lane positions, driver's face) [64].

The majority of the studies on driver's reaction from vehicle-based signals are focused on steering and lane changing or speed measurements. Steering feel is the relation between the applied steering wheel torque and the resulting steering wheel angle [33]. Steering a car requires visual information from the changing pattern of the road ahead. There are many theories about what features a driver might use, and recent attempts to engineer self-steering vehicles have sharpened interest in the mechanisms involved. However, there is little direct information linking steering performance to the driver's direction of gaze. According to Land and Lee [39] drivers rely particularly on the "target point" on the inside of each curve, seeking this point 1-2 seconds before each bend and returning to it throughout the bend. From the research of McRuer and Weir [46], it was found that the driver is assumed to observe deviations from the intended maneuvering conditions at some distance ahead of the vehicle and to correct proportionally in steering after some delay.

Driving is traditionally seen as a visually dominant task and most driving models are limited in describing responses to visual feedback. However, drivers also rely on neuromuscular and vestibular feedback. Recently kinesthetic models propose that a driver responds to steering wheel forces not only cognitively but also instantaneously (limb inertia and visco-elasticity from co-contracted muscles) as well as reflexively (fast responses from proprioceptive sensors in the muscles) [33].

Torkkola [71] investigated the factors that are most important in detecting driver's inattention. In a simple driving case, the running variance and the entropy of steering were the most important. However, in case Collision Avoidance Systems (CAS) were used, some other variables provided as much new information as the original signals, such as lane position and acceleration pedal. Steering wheel variance continued to be the most important variable related to driver's inattention.

An interesting system that can collect vehicle-based signals is the CAN-bus application, especially if the data are combined with the GPS position of vehicles. For example, an abrupt steering maneuver may indicate an obstacle on the road, windscreen wiper usage can indicate adverse weather (e.g. rain) and activation of ABS might be an indication for a slippery road surface [31]. Furthermore, CAN bus signals, which can be used to measure parts of the driving behavior, are ideal to measure driving behavior in real driving conditions.

Vehicle trajectory data can be collected by capturing video from a high viewpoint, which provides insight into the behavior of drivers both longitudinally and laterally [24]. From the videos, the headway can be observed as well as the distance from the lead vehicle on acceleration. An advantage of this method is that more than one drivers can be observed at the same time and at the same conditions. Another example of remote sensing is the use of cameras alongside the road. However, this method does not allow the collection of information on personal characteristics of the drivers (e.g. gender, age, driving experience) and of in-vehicle distractions.

2.3 Car-following models

The car-following maneuver is mainly a tactical level activity which is closely related to speed, comfort and safety. Although tactical level behavior is directly affected by strategic decisions and has to be implemented through operational control of vehicles (steering, gearing, braking), it is the main interactive interface between the driving vehicle and other vehicles and the traffic environment. So the models and algorithms on this level are always the main concern within the topic of driver modeling. In microscopic traffic simulation, researchers are especially interested in mimicking driving behavior as realistic as possible on a tactical level. Tactical models in simulation describe the driver's behavior based on the current traffic situation and focus on short-term interactions between the vehicle and its environment, without drawing details on how drivers perceive and operate. Car-following models are tactical driving models which describe the driver longitudinal behavior when following another car and trying to adapt its speed and maintain a safe distance [42].

Car-following can be regarded as a subtask of the longitudinal vehicle interaction task. In the literature, there are several mathematical, microscopic models which present the

driving behavior under different traffic flow conditions. All these car-following models are defined by ordinary differential equations describing the complete dynamics of the vehicles' positions and velocities. According to Brackstone and McDonald [6], in general three types of car-following models can be distinguished:

- stimulus-response models,

- safety-distance models,

- psycho-spacing models.

The cellular automata models, the optimal velocity/optimal control models and the fuzzy logic/rule-based models also describe the longitudinal driving task [27] but their analysis is beyond the purposes of this thesis.

Safety-distance models are static and therefore do not describe the dynamics of vehicle interactions. The first safety-distance models were based on the rule that the safe distance S with which the vehicle follows the vehicle ahead is at least the length of a car for every ten miles per hour of speed at which the vehicle is traveling [27]. Since the available data for this thesis show the interaction with the lead vehicle and the safety models are static models which do not describe vehicle interactions, they are not used in this project.

The psycho-spacing models are based on theories on perceptual psychology and they describe the behavior of the vehicles in a relative speed with relative distance plane. In these models longitudinal driving behavior is controlled by perceptual thresholds. These thresholds serve to delineate a relative speed - spacing plane (spirals) in which the driver of a following vehicle does not respond to any change in his dynamic conditions and would seek to maintain a constant acceleration [7]. On crossing one of these thresholds, a driver will perceive that an unacceptable situation has occurred and will adjust his longitudinal driving behavior through a change in the sign of his acceleration [24]. The characteristic spirals in the relative speed - relative distance plane are presented in Figure 2.3. The psycho-spacing models are higher fidelity models than the continuous models, but they show a considerable degree of variability. Hoogendoorn et al. [26] showed that the assumption of deterministic perceptual thresholds incorporated in the original formulation of the psycho-spacing models does not hold in reality. Variability within as well as between drivers may be assumed to be caused by driver characteristics as well as external conditions.

Stimulus-response models provide a continuous time description of traffic flow. Stimulus-response models are dynamic models that describe the reaction of drivers as a function of the changes in relative distance and speed to the vehicle in front. In general, the stimulus-response models and the safety-distance models in various ways try to describe the acceleration or speed of a vehicle. The drawbacks of these models are that the driver is not able to observe a stimulus lower than a given threshold and manipulate the gas and brake pedal precisely. Also, the driver can not evaluate a situation and determine
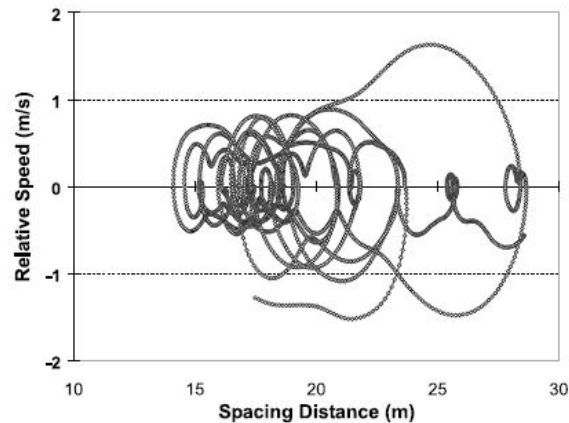
Figure 2.3: The typical spirals in psycho-spacing models [7].

the required response precisely [27].

For the parameters estimation procedure, the stimulus response models are selected since they are able to show the dynamic interactions between other vehicles in the same lane. These models are very popular in the physical and mathematical literature because they are simple to analyze and understand, and even analytical results can be derived [74]. Furthermore, models like the Helly and the IDM (Intelligent Driver Model) show better performance and are able to achieve a better fitting in data.

One of the most well-known nonlinear models in the category of stimulus-response models was proposed from Gazis [6], known as the General Motors (GM) model, and dates from the late fifties and early sixties. All car-following models developed with support from GM assume that all drivers follow the exact same driving rules. In fact, these rules may differ with different drivers, or even for the same driver and with different conditions, and in fact, possibly even to some extent with the same driver and nearly identical situations. Therefore, it is difficult to ascertain whether the behavior induced by the above models, applying the above research philosophy, is in any way "natural" [34].

The series of GM car-following models do not consider the effect of the inter-vehicle spacing independently of the relative velocity. For example, drivers will always accelerate if the relative velocity is positive and decelerate if the relative velocity is negative. However, in real driving, it is often seen that when the following vehicle is some reasonable distance behind the leading vehicle, the following vehicle can accelerate even if the relative velocity is zero [74]. The Helly model and the IDM consider the effect of the relative spacing independently from the relative velocity. Also, from existing studies [24] they have been proved appropriate in capturing the behavior of the driver from large data sets. Thus, both models are analyzed and used in this thesis.

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Before the analysis of the Helly and the IDM model, it is important to mention the three-regime models. These models not only consider the car-following behavior of the drivers but also, they used different equations for the period that vehicles move with free speed or decelerate. The different driving regimes depend on distance: for small distances, drivers try to avoid crashing into the vehicle in front, for intermediate distances they follow the vehicle in front (according to a generalization of the GM model family, while for large distances, they drive uninfluenced with their own preferred maximum speed [74]. Wagner [74] describe in detail the three-regime model and investigates the identification of the driving behavior using different models. He demonstrated that the simpler microscopic car-following models achieve better data fitting (better driving identification) than the more complicated models (e.g. the three-regime models).

2.3.1   The Helly model

The first model which is presented is the Helly model, which was first proposed by Helly [23] in 1959. In this model the driver of a following vehicle reacts to speed differences with the lead vehicle (Δv) as well as to differences between the actual distance to the lead vehicle (Δx) assessed in an earlier time ($t - \tau$) and the desired distance to the lead vehicle s_d. These differences are moderated by the sensitivity parameters α and γ. The model also incorporates the reaction time of the driver τ. The acceleration is expressed in the following equation [24]:

$$a_c(t) = \alpha \Delta v(t - \tau) + \gamma(\Delta x(t - \tau) - s_d) \tag{2.1}$$

The desired distance to the lead vehicle is linearly determined by speed represented by the parameter v. Furthermore, the desired speed also depends on a minimal stopping distance when stationary s_0. This is expressed in the Equation 2.2:

$$s_d = s_0 + h_{min}v \tag{2.2}$$

In the Equation 2.1, α and γ are parameters that have to be estimated. For the determination of α, Helly borrowed directly from earlier work (by data taken from 14 drivers [6]) the best fit parameters, almost all being produced at the coefficient of determination r^2 > 0.8 (shows how well the data points fit a statistical model), ranging from $\alpha = 0.17$-1.3, with an average of 0.5. Next, γ was estimated by setting the Δv and Δx terms to be equal and opposite (producing no acceleration) when a vehicle detects a stationary object [6]. This produced the final equations:

$$a(t) = 0.5\Delta v(t - 0.5) + 0.125(\Delta x(t - 0.5) - s_d) \tag{2.3}$$

$$s_d = 20 + v(t - 0.5) \tag{2.4}$$

Table 2.2: Summary of optimal parameter combinations for the Helly model [6].

Source	α	γ
Helly (1959)	0.5	0.125
Hanken and Rockwell (1967)	0.5	0.06
Bekey, Burnham and Seo (1977)	0.5	1.64
Aron (1988)(dec/ss/acc)	0.36/1.1/0.29	0.03/0.03/0.03
Xing (1995)	0.5	0.05

Some other estimations for the parameters α and γ are presented in Table 2.2. Aron [3] proposed different parameters for deceleration, for steady state and for acceleration.

The Helly model incorporates a threshold mechanism, whereby the driver does not reassess the required deceleration until the discrepancy between estimated and actual spacing exceeds a specified criterion. The incorporation of a threshold mechanism would appear to bring this model conceptually close to risk-threshold models of driving behavior. However, the Helly model threshold is not intended to represent a purely behavioral mechanism, since it compares the driver's estimation of spacing with the actual spacing, presumably not directly available to the driver. Therefore, while car-following models incorporate some assumptions about underlying behavioral mechanisms, they are clearly not intended to be purely behavioral models of car-following [57].

Except of the above linear form of the Helly model, there is a multi-anticipative adaptation which considers more than one vehicles ahead of the ego vehicle. Hoogendoorn et al. [28] estimated the parameters of a multi-anticipative adaptation of the Helly model using trajectory data collected with a helicopter. From the results it followed that some drivers apparently consider only the direct lead vehicle, while other drivers also consider the second and third lead vehicle. This suggests a considerable degree of variability in multi-anticipation as well.

2.3.2 The IDM model

The next model that was studied was the Intelligent Driver Model (IDM). It was developed by Treiber et al. [73] in 2000 to improve upon results provided with other "intelligent" driver models such as Gipps' Model, which lose realistic properties in the deterministic limit [20]. This model is a continuous function incorporating different driving models for all speeds in freeway traffic as well as city traffic. Besides the following distance Δx and speed v the IDM also takes relative speed Δv into account [24]. The IDM acceleration and the desired distance are given by:

$$a = a_{max}[1 - (\frac{v}{v_0})^\delta - (\frac{s_d(v, \Delta v)}{\Delta x})^2]$$

(2.5)

$$s_d(v, \Delta v) = s_0 + vT + \frac{v\Delta v}{2\sqrt{a_{max}b_{max}}} \tag{2.6}$$

The expression combines a free flow acceleration regime $a[1(v/v_0)^d]$ with a deceleration strategy $a(s_d/\Delta x)^2$. The latter becomes relevant when the actual distance to the lead vehicle Δx is not significantly larger than the desired distance to the lead vehicle s_d. The free flow acceleration is characterized by free speed v_0, maximum acceleration a_{max} and the component δ. The component δ characterizes how acceleration decreases with speed. The desired distance to the lead vehicle s_d is composed of a minimal stopping distance s_0, and a speed dependent distance vT. This corresponds in following the lead vehicle with a constant desired time headway T and a dynamic contribution which is only active in non-stationary traffic conditions. This implements an "intelligent" driving behavior that, in normal situations, limits braking decelerations to the maximum deceleration b_{max} [24].

2.4   Modeling driving behavior from vehicle based-signals

In literature different tools have been processed and a variety of approaches that have been used to determine the driving behavior. Most of the studies uses statistical tools like the hidden markov models or artificial intelligence (neural networks, genetic algorithms). The approaches that are used may vary from parameter estimation in car-following models to identification of signals or pattern recognition of maneuvers (combination of vehicle movements). In this section some of the modeling approaches that have been used in the past and their results are presented.

The Hidden Markov Models (HMMs) can be used for identifying driver's behavior from vehicle-based signals. The HMMs are probabilistic tools for studying time series data. They attracted great attention in the pattern recognition research community due to their success in a range of applications, notably in speech recognition. According to Mitrovic [47], driving actions represent patterns. Turns, for example, consist of the following actions: the driver first reduces speed and changes to a lower gear, then rotates the steering wheel, next increases speed, changes up a gear, and finally rotates the steering wheel to the other direction. This set of actions will be repeated every time a driver executes a turn.

Based on the pattern recognition concept, Mitrovic [47] measured the lateral and longitudinal acceleration, speed and slope of the vehicle to identify 7 different driving events (driving along left and right curves, turning left and right on intersections, with and without roundabouts and driving straight across an intersection with a roundabout). Each event consisted of specific states which can be observed in a plotted diagram of speed, lateral and longitudinal acceleration. Screenshots of the states lead to manual pattern

recognition. A similar study in a virtual environment, with 12 different driving maneuvers showed that the HMMs are certainly useful and capable of modeling the driving behavior of a driver [72].

According to Zou [86], measured vehicle movements and visual human behaviors are comparable to raw observations for recognition. These "behaviors" are observed as patterns of events, which include continuous trajectories or discrete sequences of measurable properties such as position, direction and speed from sensors or shape and color in images. Zou used data from vehicles (types of vehicles, location, velocity, acceleration/deceleration, distance/time to the location where roads cross), from video cameras (lighting conditions) and data for weather conditions and then he defined only three simple states (acceleration, cruising, deceleration). Using the single HMM did not provide a good fit to all sample sequences but he solved that problem by using different HMMs to model behavior characterized by different clusters (driving styles).

Dapzol [14] based on previous studies with simulated data [55] used actual vehicle data for the identification. He used in-vehicle data from cameras (front, rear, driver head and feet) and sensors to identify the state of the car (speed, lateral acceleration). The action of the driver was divided in phases and using graphical representation of the signals, he was able to identify the driving behavior. The most interesting part of this study was the separation of the action in phases. He suggested that doing this facilitated future identification of the phase when driver's behavior differentiates from the normal and activated control system on him (e.g. warning alarm). However, Dapzol did not examine the importance of each signal, but considered that all the signals are equally important in each phase.

The driver may demonstrate the same behavior in different situations or he may demonstrate different behavior in the same situation [14]. In line with Sathyanarayana et al. [63], the HMMs can model the stochastic nature of the driving behavior, providing sufficient statistical smoothing while offering effective temporal modeling, and the variations in the driving signals across the drivers can be modeled (driver identification) or suppressed (driver independent route models) according to the requirements of the desired task. They used vehicle-based signals (vehicle speed, steering wheel angle and brake force) to recognize three different maneuvers (left turn, right turn and lane changing) and detect driver's distraction in a time window of 2 and 5 seconds.

Boyraz et al. [5] combined Artificial Neural Networks (ANNs) with HMMs in order to identify the driver's behavior in an urban road from the vehicle speed and the steering angle signals. First the signals were divided in segments and then the maneuvers were recognized and classified with the use of the ANNs. The final step was to use HMM to predict the sequences of the signals coded in terms of phases which were labeled by the ANN. It was found that HMMs are promising in terms of modeling the maneuvers once they have been broken down into phases corresponding to the physical meaning of

the maneuvers. Dapzol [14] does not agree with the use of ANNs in identifying driver's behavior since neural networks do not calculate the consequence of the criteria on all road networks. Their main disadvantage is the obscure nature of the learned system which is like a black box. The model that matches the data cannot be interpreted by an analyst. Therefore, such a system cannot be improved by inserting an expert's knowledge.

The same method (ANNs) was used by Othman et al. [52] in order to check the inattention of the driver. In that study, the behavior of the driver without secondary tasks (baseline scenario) and also with secondary tasks was identified. They used actual data from two cameras (showing the road in front and the driver) and vehicle data (speed, steering angle and pedal pressure). The pedal pressure was calculated as the sum of the gas pedal (considered positive) and the brake pedal (considered negative). They inserted the speed and pedal operation as an input to their model and the steering angle as an output. The predicted results of the model were compared with the actual measurements of the steering angle. The same study was performed by Wefky et al. [76] using ANNs and vehicle observations.

Other tools to identify the driving behavior are the use of derivative methods and evolutionary algorithms. In derivative methods the optimal point is determined by iteratively search in the directions related to the derivative of the objective functions. Evolutionary-based methods have been extensively used in solving optimization problems due to their ability in searching global optimum. The most widely used methods include Genetic Algorithms (GAs), Simulated Annealing (SA) and Particle-Swarm-based Algorithms (PSA). These methods do not need derivative information. Instead, they rely on the repeatedly evaluation of the objective function based on some heuristic guidelines motivated by the wisdom of nature, such as biology evolution, physical phenomena and social behavior of animals and insects.

Tanaka [69] used artificial intelligence to create a methodology that matches data points. Four car-following models with ANN structure were developed with various input variables in the car-following behavior. A four-layer ANN structure was set up and a GA and back-propagation methodology were utilized for determining the synaptic weights in the models. However, the models sometimes had a difficulty in learning such enormous number of raw data points. For the evaluation, a simple car-following model was used. It was found that ANN models were successfully developed with data conversion without deteriorating the original data quality. Through comparison of the results of the four ANN models, it was conjectured that the accelerations of the following vehicle and leading vehicle can also become key input variables for improving the modeling of car-following behavior.

Ma [42] used data collected from real traffic using an advance instrumented vehicle to identify driver-following behavior. After extensive data analysis and smoothing, a least square estimation deviation between the real and modeled acceleration outputs was used

to estimate the parameters in a car-following model with the Kalman-Filtering algorithm (an algorithm that uses a series of measurements observed over time, containing noise and other inaccuracies to produce estimates of unknown variables). Then, five regimes were considered, including following, acceleration, braking, approaching and opening and it was tried to identify the regime properties from collected real data by exploring and classifying the patterns with the use of fuzzy logic. The overall conclusion was that driving behavior shared apparent non-linearity and stage adaptivity.

Angkititrakul et al. [2] used two different methods in a car-following situation in order to relate vehicle-based signals (brake and gas pedal, velocity) and distance with vehicle dynamics. First the Gaussian mixture model was used in order to identify the pedal operation from the relative distance. Then, the PWARX model (piecewise auto-regressive exogenous model) was used for the same purpose. In that model, four different modes were created: collision avoidance mode, approaching mode, following control mode I, following control mode II. The data were collected from tests in the field from 77 drivers in a variety of driving environments and traffic conditions. In the end, the error between the predicted and observed pedal operation was calculated. It was revealed that the smallest the prediction time, the highest the SDR (highest SDR means better performance) and also the gas pedal operation was better predicted than the brake pedal operation. In the same study an adaptive model was created that was used to capture the heterogeneity between drivers.

Ma and Andreasson [43] used nonlinear optimization methods to minimize the summation of squared errors between the model output and the real output data. For that research they used a car-following model (the GM) and they assumed fixed reaction time. They found that the car-following model was able to describe the stable car-following regime. Rakha et al. [56] used naturalistic driving data from a 100-car study to calibrate four different car-following models, one of them being the IDM model. They searched for the calibrated parameters of the car following models that matched the simulated with the observed behavior of the driver. To compute those calibrated parameter values, they generated observed and simulated vehicle trajectories, set limiting bounds on the parameter values, defined an error function and selected an optimization method to minimize the error objective function.

Brockfeld et al. [9] cross compared different microscopic traffic flow models using data from ten car-following experiments. To calibrate the models, the data of the leading car were fed into the model under consideration and the model was used to compute the headway time series of the following car. The deviations between the measured and the simulated headways were used to calibrate and validate the models. They found that the differences between individual drivers are larger than the differences between different models. Hoogendoorn [24] also estimated the parameters in two car-following models, the IDM and the Helly model, with simulated data under adverse conditions. He used a deviation of a statistical parameter approach which enabled the statistical analysis of the

model estimates and the cross-comparison of models of different model complexity. The validation process gave acceptable errors from 17% to 22%. Also he used Bayesian networks to predict action points in relative speed - relative distance plane and the approach performed relatively well. Schultz and Rilett [65] proposed a methodology to introduce and calibrate a parameter distribution using measures of mean and variance to generate input parameters for car-following sensitivity factors in microscopic simulation tools. The approach was applied using a microscopic traffic simulation model (CORSIM) and calibrated through an automated genetic algorithm.

2.5 Brief synopsis and assessment

From the literature analysis, it is shown that the components of the driving environment and their relation to the driver's behavior has been extensively studied. A lot of researches have revealed that there is a strong connection between the outside environment and the driver. Many researchers [24, 29, 54, 66] have also related the behavior of the driver with specific conditions in the outside environment (congestion, heavy vehicles, fog and rain) and described the consequences of that relationship. Some research is also available about the connection of in-vehicle factors and driver-related characteristics with the driving environment.

In order to identify the driver's behavior from vehicle based signals, GPS data, cameras, data from instrumented or simulated vehicles can be used. Most studies focus on the behavioral changes of the driver by examining the steering and lane changing of the vehicle. Other vehicle-based signals such as relative distance and speed are used in a limited number of occasions since it is difficult to obtain such data. Most data in the literature were selected from simulation experiments.

The car-following models can be categorized in stimulus-response models, safety distance models and psycho-spacing models. The stimulus response models offer better fitting in driving data and two models of this category are selected and are analyzed: the Helly model and the IDM model. The first includes the minimum stopping distance, the minimum headway and the sensitivities of speed and distance differences as parameters. The latter includes the free speed, the minimum stopping distance, the maximum acceleration and deceleration as parameters. Both models have limitations since they are car-following models and they are able to identify the driver's behavior only under car-following conditions. Despite their limitations, their selection for this thesis is made based on their simplicity and their ability to fit well in long driving data. Furthermore, the interest of this thesis is focused on the methodology for identifying the driving behavior and the action points and simple models are needed in order to assess the reliability of the proposed mathematical framework.

For the modeling of the driver's behavior, pattern recognition techniques or parameter

estimation approaches have been used. The Hidden Markov Models have been performing very well in the recognition of driving patterns. The Artificial Intelligence methods (neural networks, genetic algorithms) and some statistical approaches were mostly used for the estimation of the parameters of car-following models.

In this project, actual vehicle-based signals are used to identify the normal behavior of the driver. This offers greater efficiency and accuracy in the research results in contrast to the simulation data which offer a limited selected number of driving conditions (human directed and not natural). Both the Helly model and the IDM model are examined in the next chapters. Then, the parameters of the car-following models are estimated by using Artificial Intelligence and statistical optimization approaches. The parameter estimation method is preferred over the pattern recognition since it offers greater flexibility, the movement of the vehicle is directly identified and not the whole action (combination of different movements, e.g. change of lanes). In the end, the observed behavior is related with changes in the road environment and the traffic flow.

Chapter 3

Data analysis

In order to determine the reaction of the driver, a number of indexes can be measured inside the vehicle: speedometer, brake usage, steering position, rpm, indicator usage, fuel consumption, etc. The data that are analyzed in this thesis are vehicle-based signals and on-vehicle camera data. The vehicle-based signals that are used for the identification of the driving behavior are the vehicle speed, the steering, the longitudinal acceleration, the relative speed and distance. The data that are used, come from driving experiments in the wider region of Helmond - Eindhoven (the Netherlands) [70] and are analyzed in Matlab.

3.1 Data collection process

In total, three different tests were conducted and both the vehicle-based signals and the camera data are analyzed. For the tests, two cars were used, a Volkswagen Golf which was the lead vehicle and a Toyota Prius (Figure 3.1) which was the follower/ego car that collected all the data. The lead car did not use any additional technology since its role was to create the desired car-following situation and not the data collection. The ego car used the Mobileye, a smart mono camera, which offers a safety solution for collision prevention and mitigation. The Mobileye C2-270 system includes a smart camera located on the front windshield inside the vehicle. It utilizes Mobileye's vehicle, lane and pedestrian detection technologies to measure the distance to vehicles, lane markings and pedestrians, providing the driver with life-saving alerts [44]. TNO [70] has a special version of the Mobileye, whereby more information is being released than with the original C2-270 system. Figure 3.2 shows a visualization of the logged data. The frequency of the data collection process was 100 Hz, that means that an incoming signal was recorded every 0.01 seconds.

For one of the experiments the Adaptive Cruise Control (ACC) feature was enabled. This system offers the possibility to drivers to remain at cruising speed while keeping a safe distance from the closest in-path vehicle. While it is branded as a comfort feature, ACC actually enhances safer driving by reducing driver fatigue and minimizing accident

Figure 3.1: The ego car that was used in the experimental process.
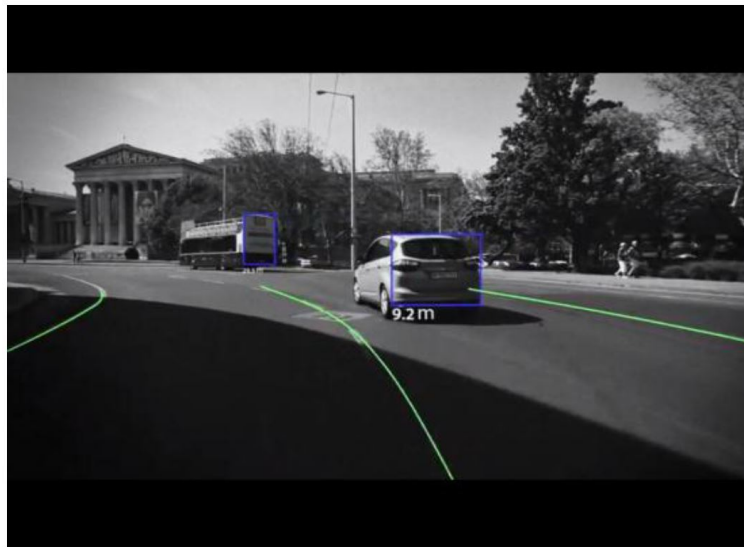
Figure 3.2: Visualisation Mobileye output [44].

prone situations. The control of the vehicle required for ACC is based primarily on the range (distance) and range-rate (relative velocity) to the closest in-path vehicle [48]. The ACC uses radar and these signals were also recorded. In general, the signals from the radar present higher accuracy than the camera signals (Mobileye). Although the radar signals were not used in this thesis, they are recorded and are available for future research.

Furthermore, two cameras were placed in the ego vehicle, inboard recording the driver's actions and outboard recording the road in-front of the ego vehicle. The HD video from the cameras enables one to re-watch situations. In watching the video from the outboard camera, it became possible to measure the effect of the driving behavior to the environment. In addition, the pictures taken with the camera allowed further clarification of the conditions that had occurred. The videos from the inboard camera were not used in the current thesis, but they would be useful in future studies which analyze the behavior of the driver from a psychological perspective (for example how the driver performs inside the vehicle, his face expressions).
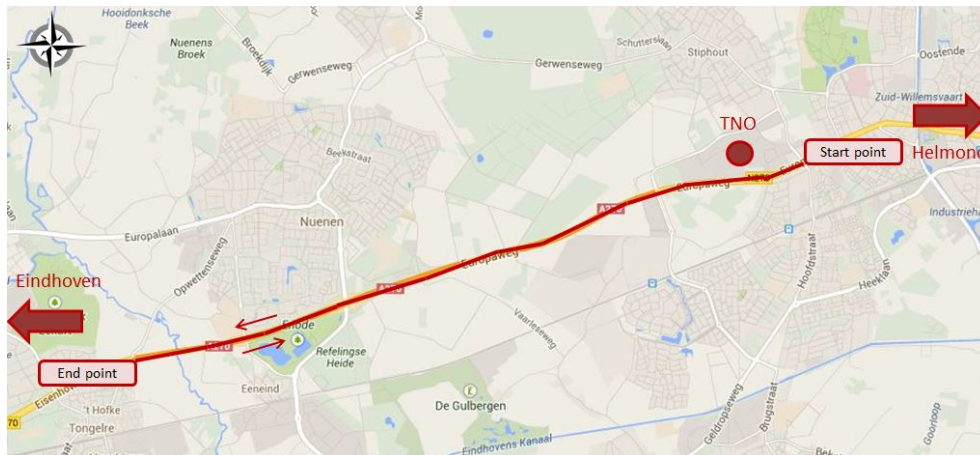
Figure 3.3: The experimental area of the collection process with extreme driving and ACC (October 3rd and 15th).

The first experiment was conducted on Wednesday October 3rd, 2013. The starting time was around 12:00 and the end time was around 14:00. In this experiment, two cars were used and the car-following task was tested in relation to extreme changes in the driving behavior of the ego vehicle. The experiments took place mainly on the A270 between Eindhoven and Helmond but also in some nearby routes (A270 is shown in Figure 3.3). The route was driven several times and the driver had perfect knowledge of the route and the vehicle. The weather conditions were good. The driver's age was in the age group of 45-55 years old and in the car there were two more passengers.

The second experiment was conducted on Tuesday October 15th, 2013. The starting time was 14:40 and the end time was 15:20. The data collection started on the highway Europaweg (N270/A270) between Hortsedijk till Wolvendijk, with the total length of 8 kilometers (Figure 3.3). The aforementioned highway is located between the cities of Eindhoven and Helmond, near TNO Helmond. In that experiment, both cars were used and the car-following task was tested when the ACC was used and the ACC was disabled. The route was driven several times and the driver had perfect knowledge of the route and the vehicle. The weather conditions were not very good as it was slightly raining and winding. This did not influence the data collection process but it is mentioned here in case future research is conducted and the current results are compared with data received under different weather conditions (maybe a different driving behavior is observed due to different weather conditions). The driver's age was between 45-55 years old (the same driver as in the first experiment) and in the car there was one more passenger. For that experiment, vehicle-based signals were collected. Unfortunately, there was not possible to collect camera data on that experiment, but the car passenger kept written notes.

In the third and most important test, no experiment was conducted, only normal driving. Thus, only one car was used and the driver was advised to drive normal like there was no data collection process going on. The tests took place on October 22nd, 2013 in the

Table 3.1: The data collection experiments.

Date	Region	Driver Age	Gender	Data
October, 3	A270	45-55	Man	Vehicle-based signals, videos
October, 15	A270	45-55	Man	Vehicle-based signals, written notes
October, 22	A67 and A2	35-45	Man	Vehicle-based signals, videos
October, 23 (morning)	A67 and A2	35-45	Man	Vehicle-based signals, videos
October, 23 (evening)	A2 and through Nederweert	35-45	Man	Vehicle-based signals, videos
October, 24	A2 and through Nederweert	35-45	Man	Vehicle-based signals, videos

evening, on October 23rd, 2013 in the morning (from 6:30 until 8:00) and in the evening (from 16:30 until 18:00) and on October 24th, 2013 in the morning. The time periods that were selected for the tests were peak-times since most of the people used to go to/return from their work at that time. The data collection process was conducted on the A67 and A2 (Figure 3.4) on the 22nd and 23rd in the morning and on the A2 and through Nederweert (Figure 3.5) on the 23rd in the evening and on the 24th. Each route was driven only once, but the driver had perfect knowledge of the route. The weather conditions were normal and both vehicle signals and camera data were collected for those tests.

The age of the driver was between 35-45 years old and there was a passenger on the car between Maasbracht and Helmond (as it can be seen in the maps). The driver used the instrumented vehicle for the first time in this test. As a result he didn't have a perfect knowledge of the vehicle and this had a small effect on the collected data. For example, he was braking more often than usual when the relative distance was decreasing or when the lead vehicle was braking. Furthermore, he was not used in the existence of the cameras inside the car and he turn the outboard camera to the inside of the vehicle which resulted in a significant loss of recorded videos for one of the testing days.

The data collection tests are summarized in Table 3.1. Only two drivers were used for the tests. The gender of both drivers was the same while their age was different. The variability in the age and gender differences of the drivers was not sufficient to extract any conclusions for the heterogeneity in the driving behavior. Hence, the heterogeneity within different drivers is not studied in this project.

3.2   Statistical analysis

In this section, the collected data are presented and analyzed. The data analysis results are shown separately for each experiment and the data from each test are assessed. For the convenience of the reader, only two data sets from each test are chosen and presented in this report, but the same analysis was conducted for the rest of the data sets.

The Mobileye system collected a large number of signals for the ego vehicle. Six signals were selected and were analyzed in order to assess the quality of the collected data. Those signals are the longitudinal velocity, the longitudinal acceleration, the relative velocity,
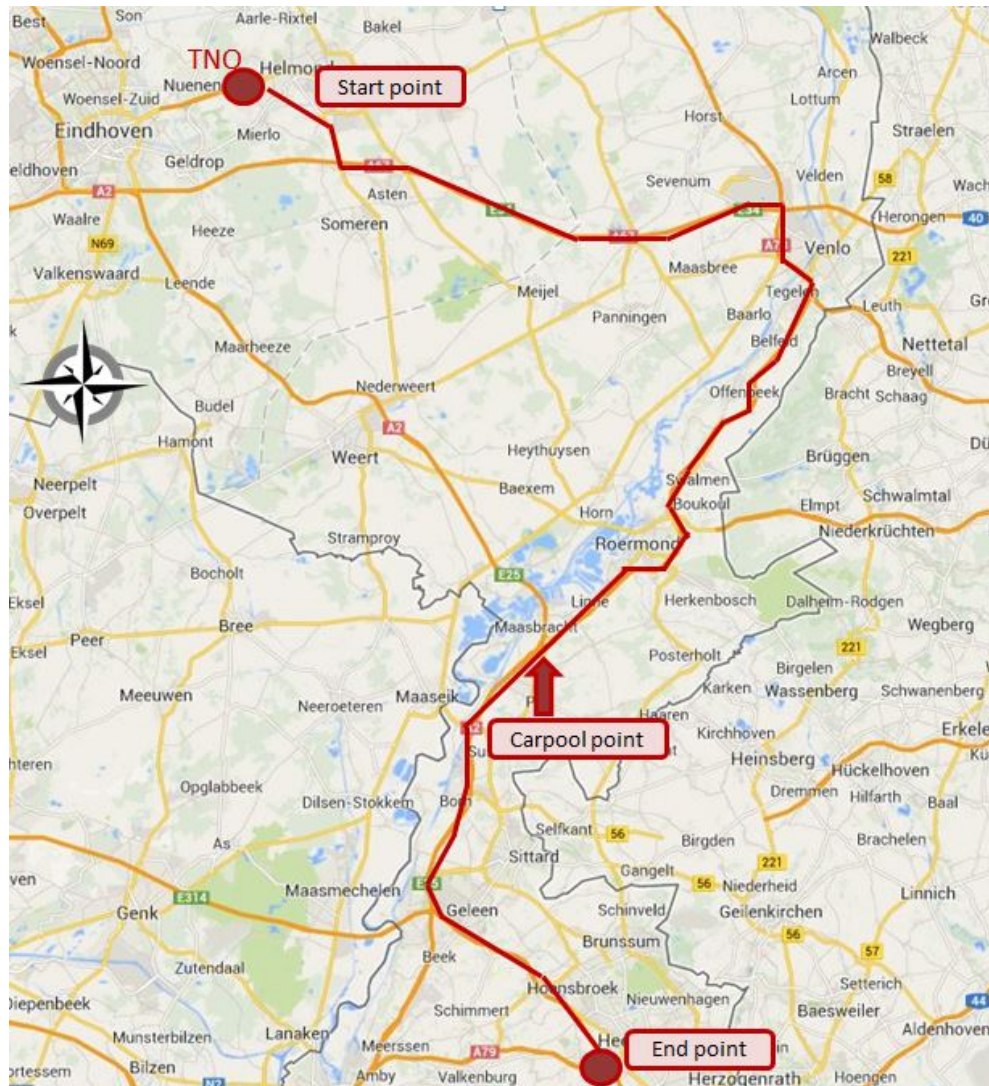
Figure 3.4: The experimental area of the data collection process with normal driving (A67 and A2).

the relative distance, the time headway and the steering of the ego vehicle (Table 3.2). The relative velocity, the relative distance and the headway are related with the lead vehicle. Those signals are used in the parameter estimation model in the next chapter as input data.

3.2.1   Car-following with ACC

The scenario that was studied was a simple car-following situation, where the ego car attempted to keep a constant distance with the lead vehicle. The lead car was asked to have a different behavior in every round in order to test different car-following conditions. In some of the rounds, the ACC system was used in order to collect data that fit better the estimation process. The ACC presents a consistent behavior throughout time since it
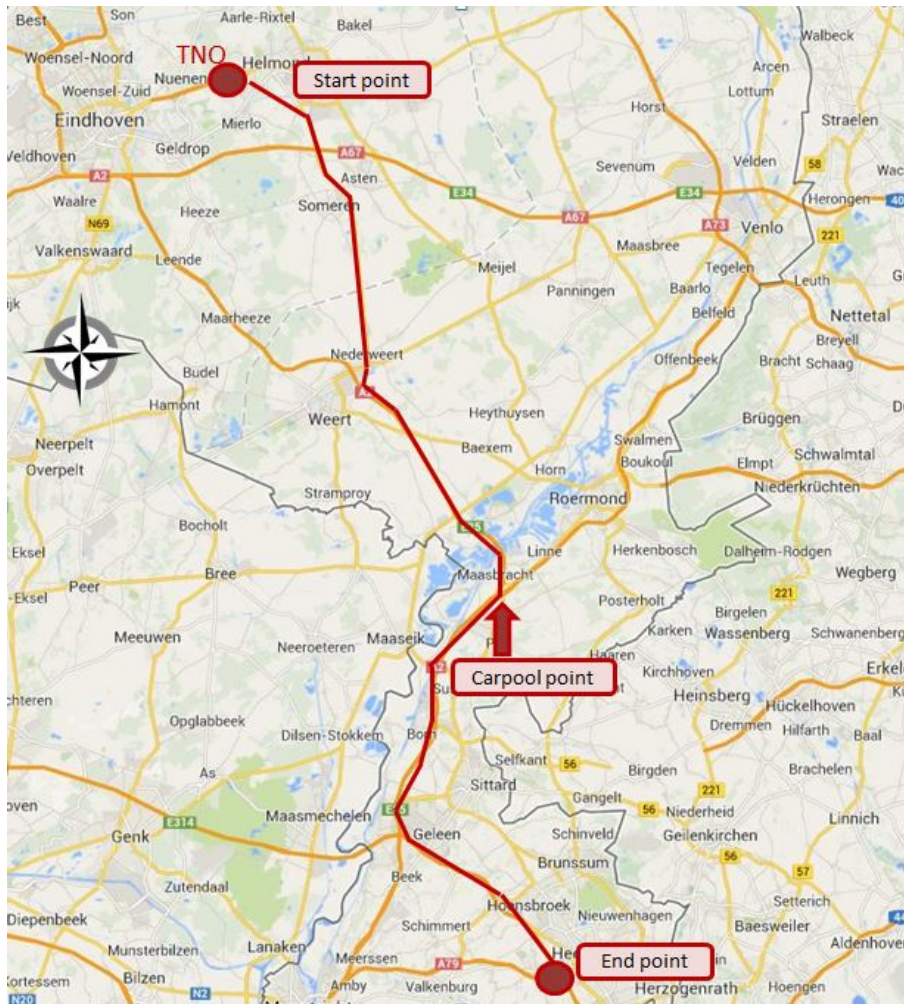
Figure 3.5: The experimental area of the data collection process with normal driving (A2 and through Nederweert).

is not influenced from external factors as the driver does. Hence, it is expected that the proposed system would identify a constant driving style while the ACC is used (a constant set of parameters to match the observed and the calculated signals). If the identification of the driving behavior is successful with the use of the ACC, then the proposed system can be used to identify normal driving behavior. In other words, the ACC is used as a performance indicator of the proposed parameter estimation system, thus the data from that experiment are used to calibrate the system.

In the experiment, the ACC system kept a constant distance between the two vehicles and it was set in scale 3, which was the largest possible distance that it could held (50 meters from the leadr vehicle). The distance kept by the ACC is independent of the speed with which the vehicle is moving. The ACC accelerates and decelerates the car so that the relative distance with the lead vehicle remains constant. The data sets that were collected, the conditions that were recorded and the validity of the data sets for the

Table 3.2: Signals selected for the statistical analysis and the parameter estimation system.

Signals
Longitudinal Velocity
Longitudinal Acceleration
Relative Velocity
Relative distance
Time headway
Steering

Table 3.3: The data sets of the ACC-driver testing on October 15th.

Data sets	ACC	Condition tested	Validity
1	On	Constant speed 90 km/h (lead car)	Yes
2	On	Constant speed 80 km/h (lead car)	Yes
3	On	Constant speed 100 km/h (lead car)	No, incident on the road
4	On	Constant speed 90 km/h (lead car)	No, speed limits forced variable speed
5	On	Constant speed 90 km/h (lead car)	No, speed limits forced variable speed
6	On	Variable speed 80-120 km/h (lead car)	No, incident on the road
7	On	Variable speed 80-120 km/h (lead car)	80-120 km/h
8	Off	Variable speed 80-120 km/h (lead car)	80-120 km/h

estimation procedure are shown in Table 3.3.

From the data sets that were collected for this experiment, the last two are presented in this report and are analyzed. The reason for that selection are the identical conditions that occurred in those data sets such that only the use of the ACC is different and can be assessed. Furthermore, in those data sets the cars do not keep constant speed and they can be used in the estimation approach in the next chapter. In contrast, the data sets 1 and 2 had almost a constant speed, relative distance and velocity and the parameter estimation fails due to limited input difference.

On the last two rounds, the driver of the lead car was requested to use variable speed between 80 and 120 km/h. The ego car tried to keep a constant distance with the lead vehicle. In the last data set 8 the ACC system was turned off. The mean values of the signals in data sets 7 and 8 are presented in Table 3.4. The average speed and its variability is almost the same in the situation of the ACC and the case when the driver is keeping a constant distance. This is also observed in Figure 3.6(a). The average speed of the ego vehicle is almost the same as the average speed of the lead vehicle in both cases (ACC and driver) as it is observed from Figure 3.6. The standard deviation is very high in both data sets since the experiment requested variable speed (speed that changes throughout the time). The headway and the relative distance (Figure 3.7(a)) are higher when the ACC is activated and this leads to the conclusion that the driver fails to keep the requested speed and approaches more than the initially defined value. The relative velocity takes values around zero (Figure 3.7(b)).

Table 3.4: Mean and standard deviation of signals in data sets 7 and 8 of the ACC-driver testing on October 15th.

Signal	Data set 7	Data set 8
Longitudinal velocity of ego car (km/h)	86.66 (23.96)	84.84 (24.34)
Longitudinal velocity of lead car (km/h)	88.18 (20.71)	84.48 (26.60)
Headway (sec)	1.77 (0.68)	1.16 (0.57)
Relative velocity (m/s)	0.26(2.26)	0.11 (1.44)
Relative distance (m)	51.08 (17.19)	36.42 (13.93)

(a)   (b)
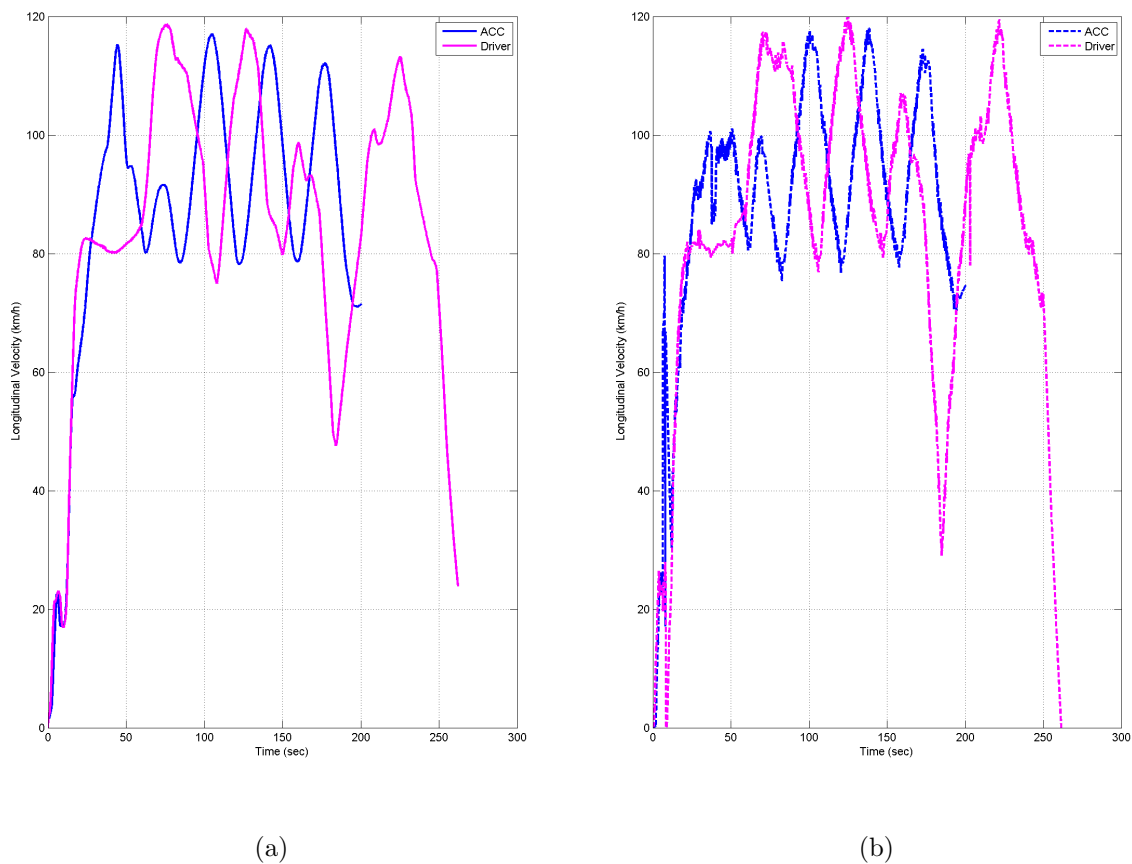
Figure 3.6: Velocity of the ego vehicle(a) and velocity of the lead vehicle (b) in data sets 7 (ACC) and 8 (Driver) on October 15th.

Figure 3.8(a) shows that the driver keeps lower distance with its lead vehicle even in higher speeds. In Figure 3.8(b), it is observed that a circle pattern is created for the two situations and it is almost the same regardless the use of the ACC system. In Figure 3.9 the relative velocity is plotted in relation to the relative distance and the speed. It can be seen that a spiral shape is created. The shape of the plot was expected and it is explained by Barckstone et al. [7]. They have plotted Figure 2.3 which resembles the shape of the

(a)   (b)
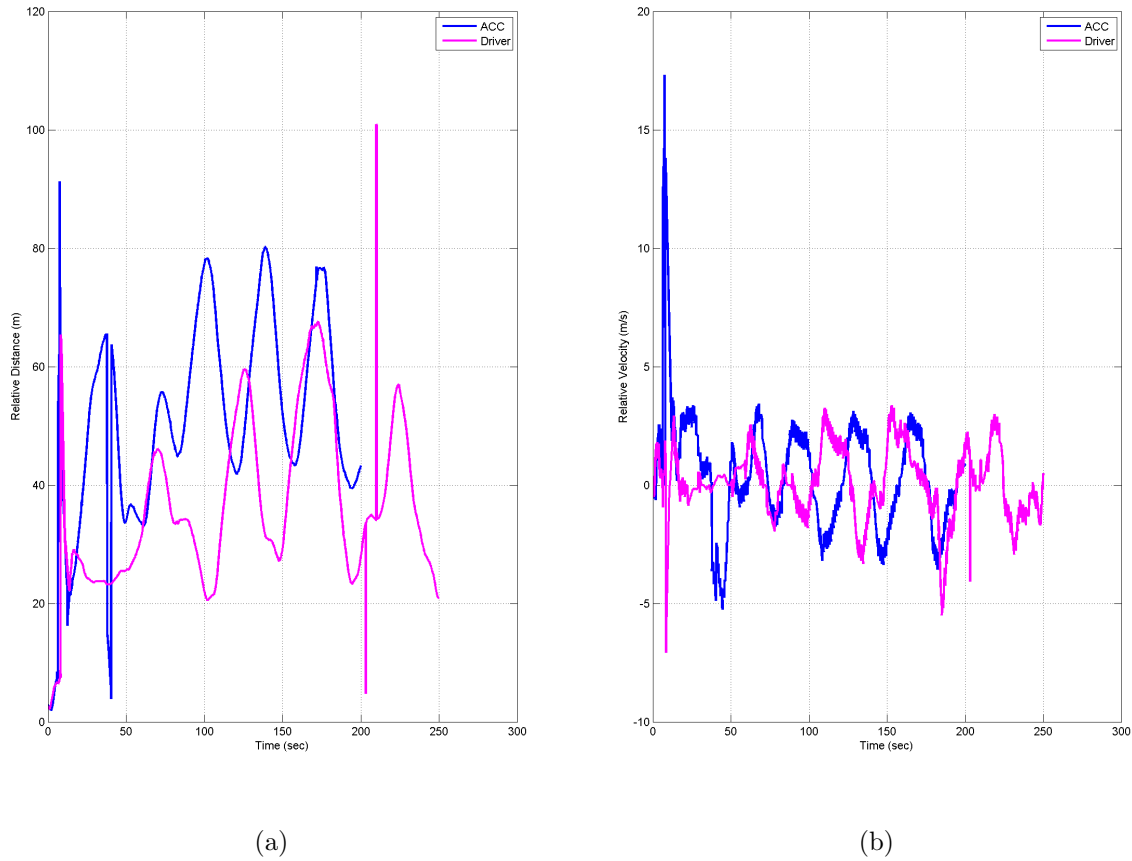
Figure 3.7: Relative distance (a) and relative velocity (b) in data sets 7 (ACC) and 8 (Driver) on October 15th.

spirals in Figure 3.9. According to the theory of psycho-spacing models, the lead vehicle has a constant speed that the follower catches up with a constant relative speed. As long as spacing is larger than a threshold, no response will occur. If the absolute value of Δv is smaller than a certain boundary value, there is also no response because the driver does not perceive Δv. The threshold value is not constant, but depends on Δv.

The ACC formulates a clear spiral for all the time that the vehicle is driving. In contrast, the driver formulates almost two spirals, one behind the other. Regarding the action points, it is expected that the ACC system can have a constant set of parameters for the whole time period of driving and no action points since the driving conditions are kept constant. The driver seems to have an action point, a threshold where he passes from one spiral to the other. Thus, it is expected that two set of parameters would be identified (one action point).

The cumulative probability distributions of the headways and the speeds in data sets 7

(a)   (b)
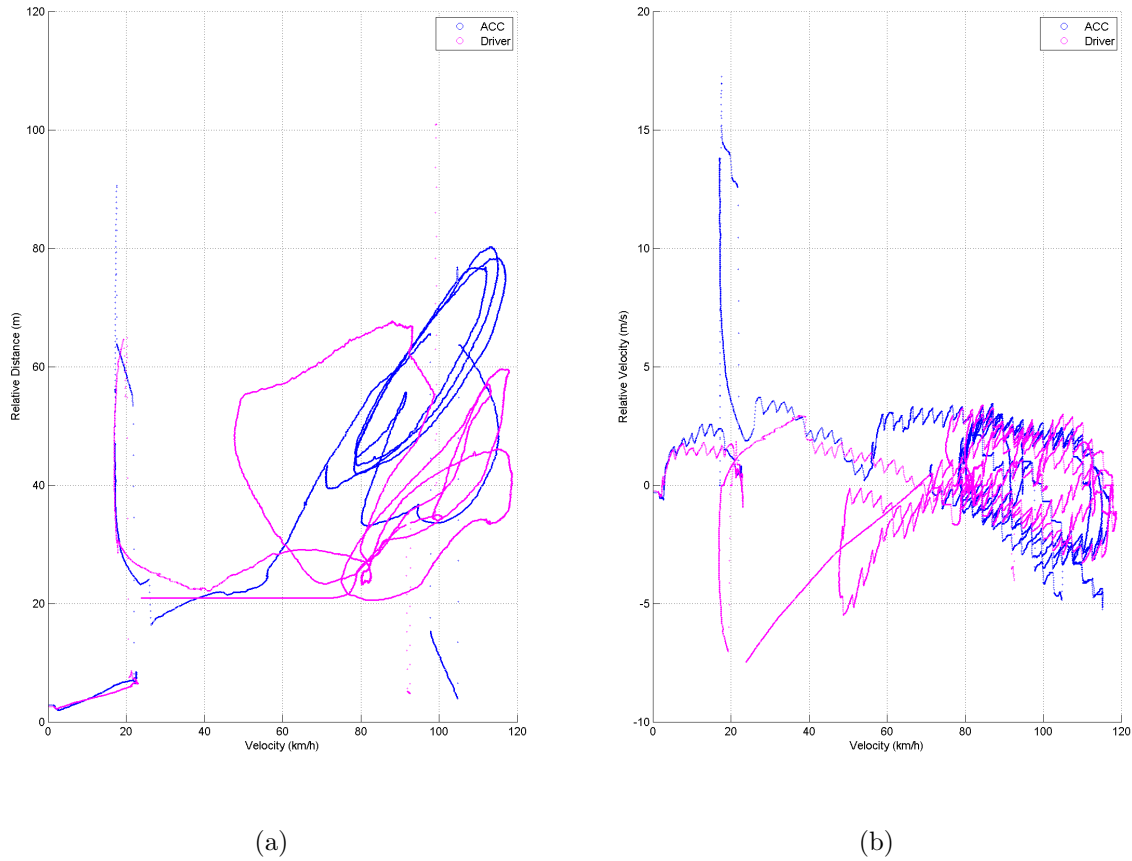
Figure 3.8: Relative distance (a) and relative velocity (b) in relation with velocity in each moment in data sets 7 (ACC) and 8 (Driver) on October 15th.

and 8 are created (Figure 3.10). The normal distribution is also plotted for the baseline situation where the driver takes decisions and the ACC system is deactivated. In the headway distribution the normal distribution does not fit very well. The negative exponential distribution is used more often in the literature [85] for headway distributions. On the other hand, the normal distribution fits pretty well in the distribution of speeds and this is also supported in the literature [80].

3.2.2   Extreme car-following

The scenario that was studied was extreme car-following, where the ego car was changing its behavior very suddenly and without an obvious reason. This experiment helped in clarifying under which conditions the car-following models can offer a good representation of reality and when they fail to give good results. Since car-following models are used, the proposed system is expected to work only when there is a car-following situation.
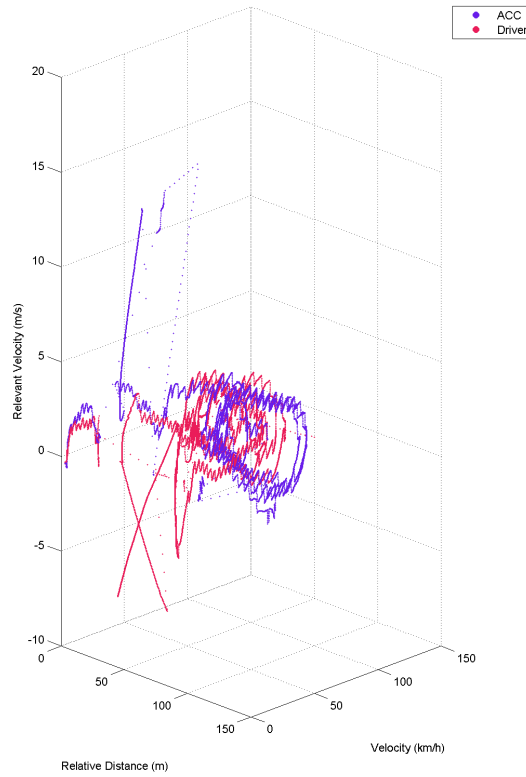
Figure 3.9: Velocity in relation with relative distance and relative velocity in data sets 7 (ACC) and 8 (Driver) on October 15th.
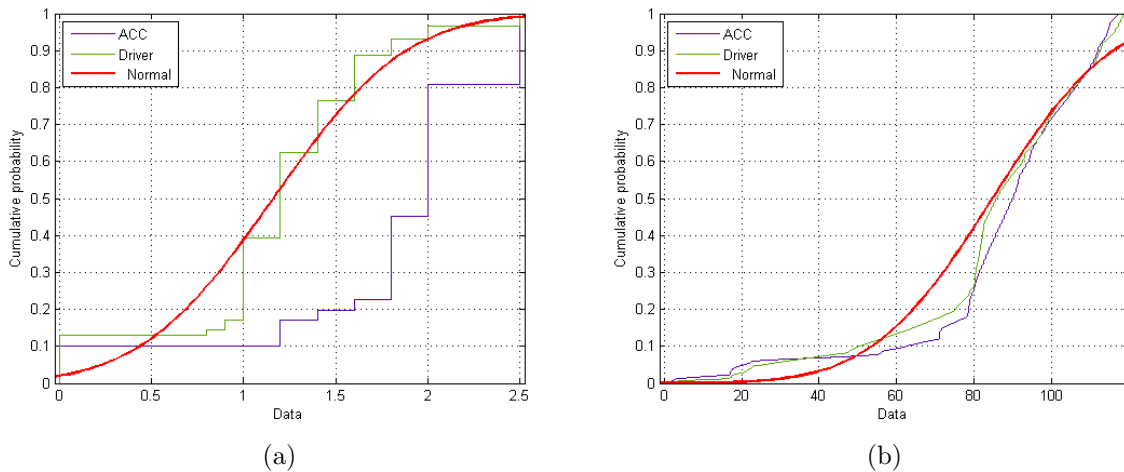
Figure 3.10: Cumulative probability distribution of headways (a) and velocities (b) of the ACC-driver testing on October 15th.

Table 3.5: The data sets of the extreme driving experiment on October 3rd.

Data sets	Validity
1	Yes
2	No, no video recorded
3	No, wrong data
4	No, wrong data
5	No, no video recorded
6	Yes
7	No, wrong data
8	Yes
9	No, wrong data
10	No, wrong data
11	No, wrong testing conditions
12	Yes
13	Yes
14	No, no data recorded
15	Yes
16	Yes

However, it was necessary to test the limits of the car-following models and find out up to what extend they are able to represent the driving task. The data sets that were collected and the validity of the data sets for the estimation procedure are shown in Table 3.5.

From the data sets that were collected for this experiment, two data sets were selected and are presented here, data sets 1 and 13. The main reason for this selection are the conditions that occurred and the results of the estimation procedure that are analyzed in the next chapter. Specifically, data set 1 is selected because the estimation cannot be totally successful and some conclusions can be derived from that data set regarding the capabilities of the car-following model. In data set 13, the estimation gives good results except from two points where changes in the driving environment occur.

In data set 1, the ego car is accelerating and in less than 10 seconds decelerating again and then again accelerating. The ego car performs an extreme driving and for that reason it fluctuates its velocity continuously. This is shown in Figure 3.11(a). The lead vehicle does not have an extreme driving and the difference in the velocity of the two vehicles can be observed in Figure 3.11(a). The unexpected movement of the ego car complicates the following task and the variation in the movement of the ego car is clearly reflected through the relative distance and relative velocity plots (Figure 3.11(b) and Figure 3.11(c)).

In Figure 3.12 the relative velocity is plotted in relation to the relative distance and the speed. It can be seen that a spiral shape is created (as expected). The different spirals show that the conditions were not constant in the road and action points are expected.

In the data set 13, the car-following task is simpler, since the ego car slows down after an
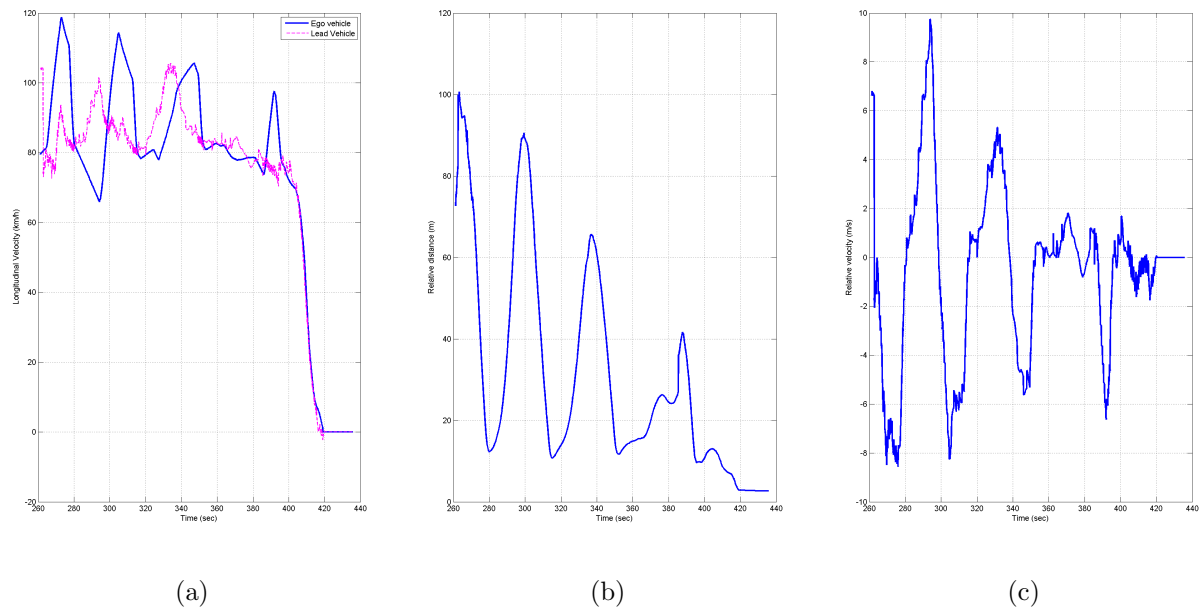
Figure 3.11: Velocity (a), relative distance (b) and relative velocity (c) in data set 1 with extreme driving on October 3rd.

extreme driving and tries to return to simple driving. Thus, the ego car does not present large variations in its longitudinal velocity and its movement is almost the same as the movement of the lead vehicle (Figure 3.13(a)). The relative velocity in this case has a small variation as it can be seen in Figure 3.13(c) and this means that the ego car does not accelerate or decelerate anymore but keeps an almost constant driving behavior. The relative distance fluctuates between 0 and 50 meters since in the beginning the ego car has extreme movement and by the end it approachs the lead car and starts a car-following task (Figure 3.11(b)).

In Figure 3.14 the relative velocity is plotted in relation with the relative distance and the speed. It can be seen that the characteristic spiral shape is created. In the beginning of the data set (first 20 seconds) the distance between the two cars was quite big until the ego car came closer and started a constant driving behavior. For that reason, two spiral shapes can be observed, one for the first 20 seconds that the ego car tries to catch the lead car and some smaller spirals for the rest of the time period.

3.2.3   Normal car-following

In the next four tests there was no experimental scenario (just simple driving), but there was data collection process going on. In Table 3.6 the analyzed data are presented. For the analysis, a moving window of 180 seconds is used (the choice of the time window is
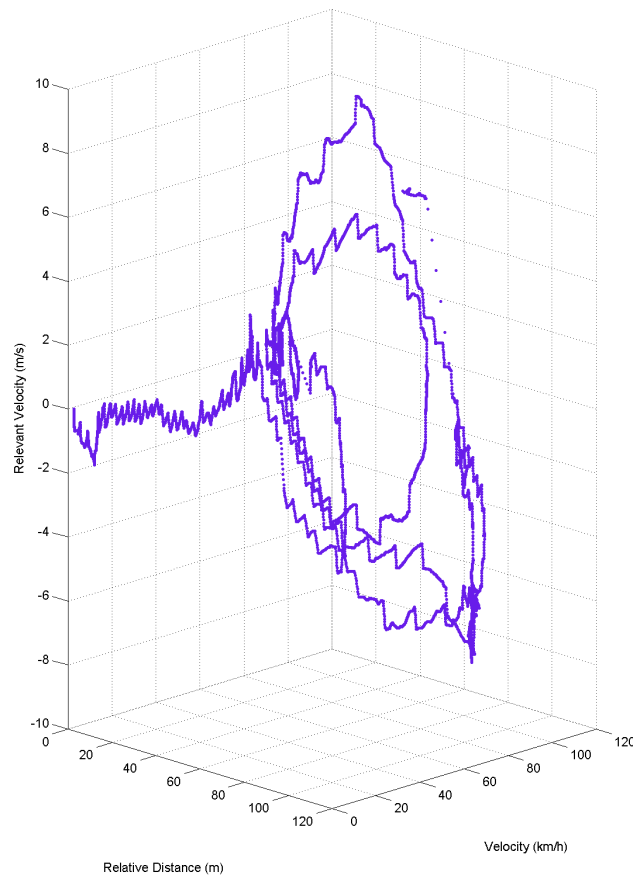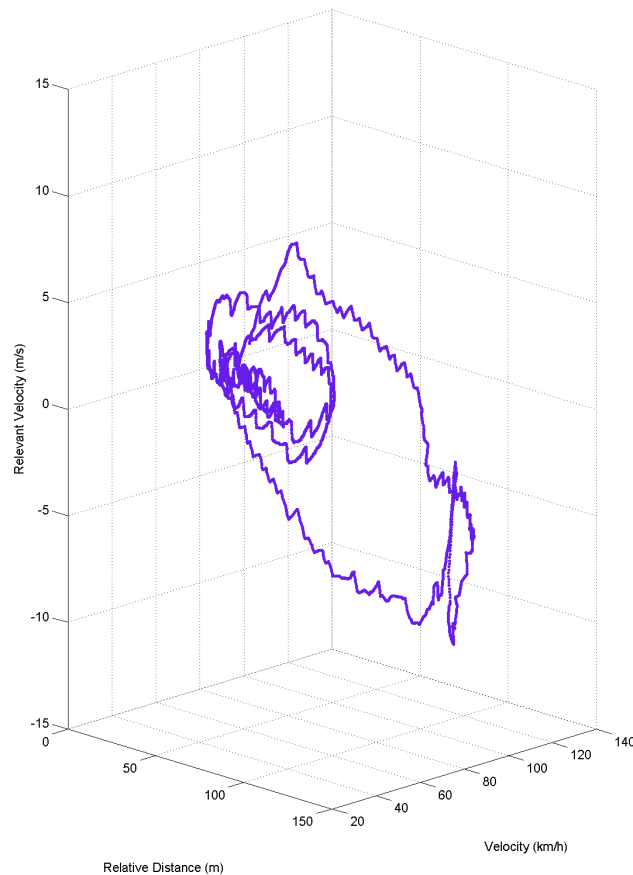
Figure 3.12: Velocity in relation with relative distance and relative velocity in data set 1 with extreme driving on October 3rd.

part of the estimation procedure and is explained in Chapter 4). Only the valid steps from each day are shown in the table. On the 23rd October in the evening, the driver stops the recorded video for some time and after that no match between the signals and the camera data can be made (the driver did not have full knowledge of the instrumented vehicle). On the 23rd October in the morning, the driver turns the camera to the inside of the car by mistake and no view from the outside environment is taken. On the 22nd and 24th October the video data are valid but some steps are omitted since the driver made some stops or moved in secondary roads for a long time without a lead car.

Here, six minutes of data are presented from two of the four testing days since their estimation results were very interesting. On the 22nd, the data collection process started from TNO in Helmond and lasted 87 minutes. The presented time period starts after 6 minutes of driving (360 sec) in a secondary road and the car enters the highway after one minute (420 sec).

(a)   (b)   (c)
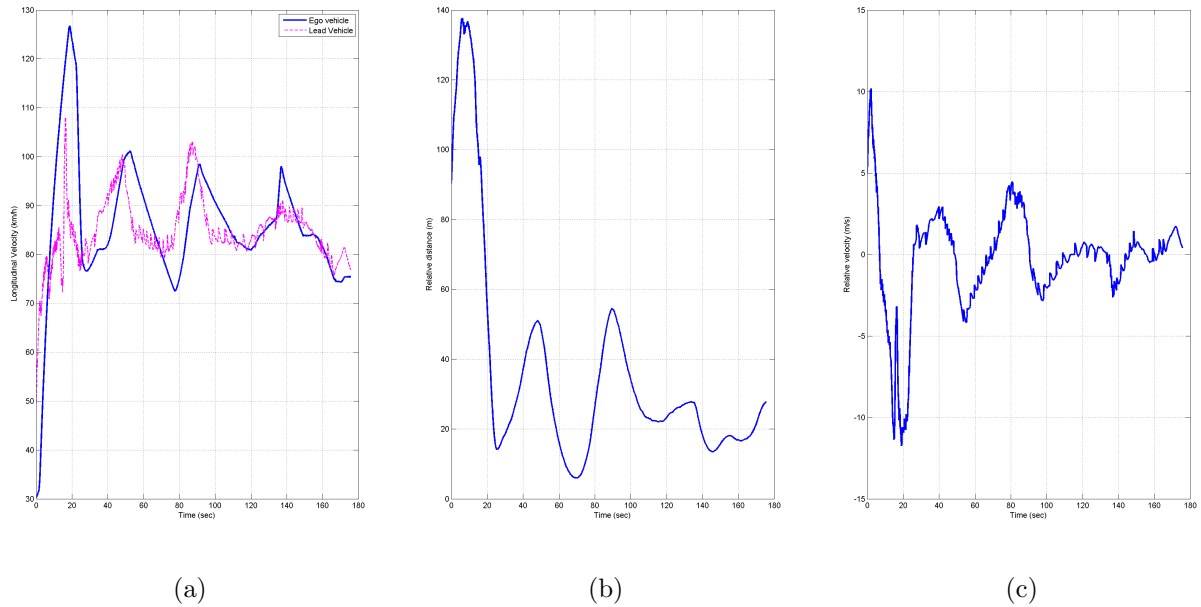
Figure 3.13: Velocity (a), relative distance (b) and relative velocity (c) in data set 13 with extreme driving on October 3rd.

Table 3.6: Overview of the analyzed data (normal driving).

	22nd October	23rd October, morning	23rd October, evening	24th October
1	360-540	1260-1440	360-540	900-1080
2	540-720	1440-1620	540-720	1080-1260
3	720-900	1620-1800	900-1080	1260-1440
4	900-1080		1260-1440	1440-1620
5	1080-1260		1440-1620	2340-2520
6	1440-1620		1620-1800	2520-2700
7	1620-1800			2700-2880
8	1800-1980			2880-3060
9	2160-2340			3060-3240
10	2520-2700			3240-3420
11	2700-2880			
12	2880-3060			
13	3060-3240			
14	3240-3420			
15	3420-3600			
16	3960-4140			
17	4140-4320			
18	4320-4500			
19	4500-4680			

As it can be observed from Figure 3.15(a), the vehicle is moving in speeds between 50-70

Figure 3.14: Velocity in relation with relative distance and relative velocity in data set 13 with extreme driving on October 3rd.

km/h and stops four times in traffic lights. The relative distance (Figure 3.15(b)) fluctuates a lot in the first 60 seconds (up to 420 sec) and the reason behind this is the movement of the car in a secondary road where the car-following task could not be applied (lead cars appeared or disappeared through side roads). From the 420 seconds and afterwards, the relative distance has a normal variation since the car is moving in a highway. The same observations are made from the plot of the relative speed (Figure 3.11(c)).

In Figure 3.16 the relative velocity is plotted in relation with the relative distance and the speed. The spiral shape is not so clear in that figure since the car changes behavior and passes from one spiral to the other. Hence, action points are expected for this data set.

On the 23rd in the morning, the data collection process faced some problems. It was dark and as a result the incoming data were wrong in some points (the Mobileye considered other objects as lead vehicles). Furthermore, after 30 minutes of driving, the camera

(a)   (b)   (c)
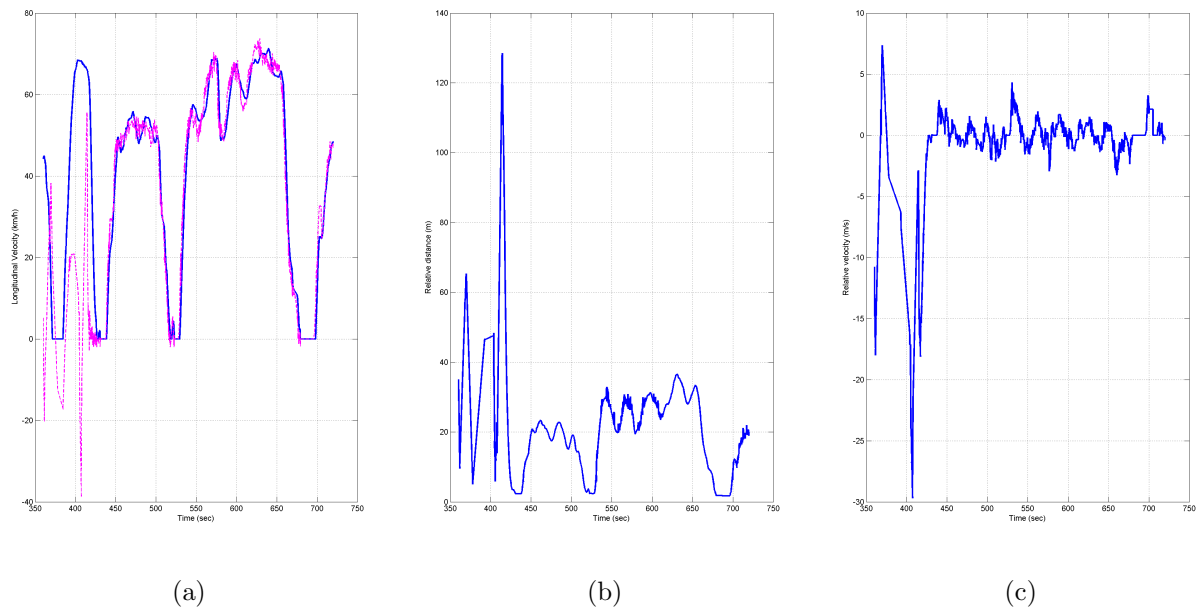
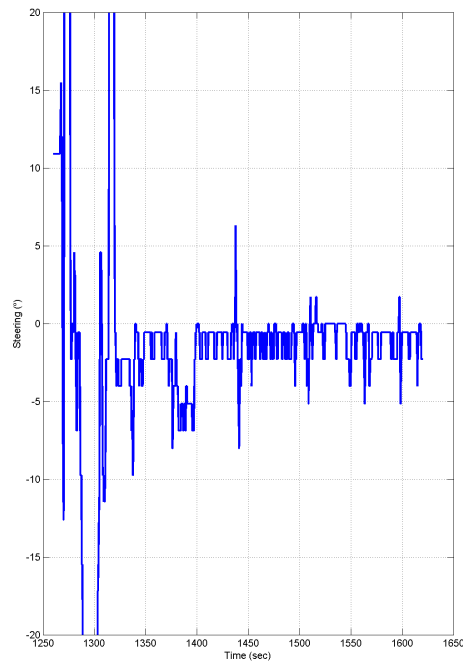Figure 3.15: Velocity (a), relative distance (b) and relative velocity (c) on October, 22nd with normal driving.

which was facing the road was turned off (the driver was inexperienced with the vehicle's instruments) and no camera data were recorded from that point and afterwards. From the first 30 minutes of driving, six minutes of data were selected and are analyzed here. This data period starts 21 minutes after the beginning of driving (1260-1620 sec).

As it can be observed from Figure 3.17(a), the vehicle starts from a traffic light, it is forced to decelerate after 60 seconds (1350 sec) due to deceleration of the lead vehicle and then accelerates again and keeps an almost constant speed of 100 km/h. The relative velocity (Figure 3.17(c)) fluctuates a lot and the variation is even more obvious in the plot of relative distance ((Figure 3.17(b)). An explanation for these variations can be derived when the steering of the vehicle is examined. The steering takes place on the seconds 1270, 1320 and 1450 while in the same seconds the large variations in the graphs are presented. The vehicle changes lanes or roads and for some seconds there is no car in front, thus the incoming data for the relative distance and speed have great variations and those variations are presented in the figures. The change of the lead vehicle can also be explained from the vertical lines in Figure 3.17(a). There, a change is made from one lead vehicle to another and as the longitudinal velocities of the lead vehicles are different, this results in vertical lines.

In Figure 3.19 the relative velocity is plotted in relation with the relative distance and the speed. The spiral shape is not so clear in that figure since the car changes lanes.
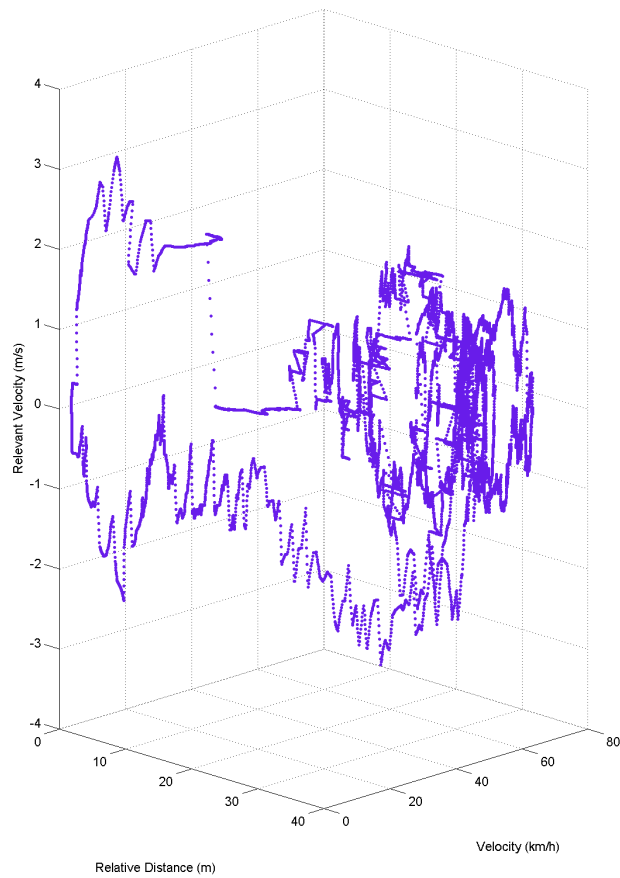
Figure 3.16: Velocity in relation with relative distance and relative velocity on October, 22nd with normal driving.

On the 23rd in the evening, the data collection process started from TNO in Helmond in the evening. The data collection process was good and the results of the data analysis are similar with the ones presented in the previous pages. On the 24th October it was early in the morning and as a result it was still dark outside and the incoming data contained some error (wrong identification of cars from the Mobileye).

3.2.4 Conclusions

The purpose of this chapter is the presentation of the data collection process and the assessment of the quality of the recorded data. Three different tests were conducted: with the use of the ACC system, with extreme driving and with normal driving. The results of the first two tests are used for the calibration of the proposed parameter estimation system and the results of the third test are used for the validation of the proposed system.

(a)   (b)   (c)
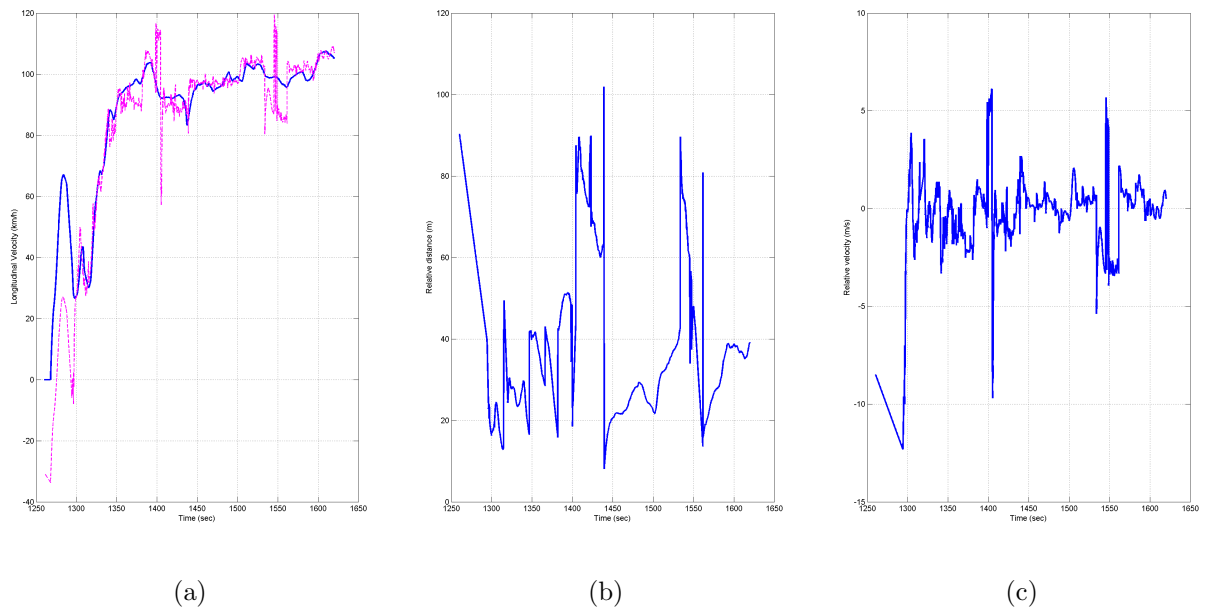
Figure 3.17: Velocity (a), relative distance (b) and relative velocity (c) on October, 23rd in the morning with normal driving.

Figure 3.18: Steering of the vehicle on October, 23rd in the morning with normal driving.

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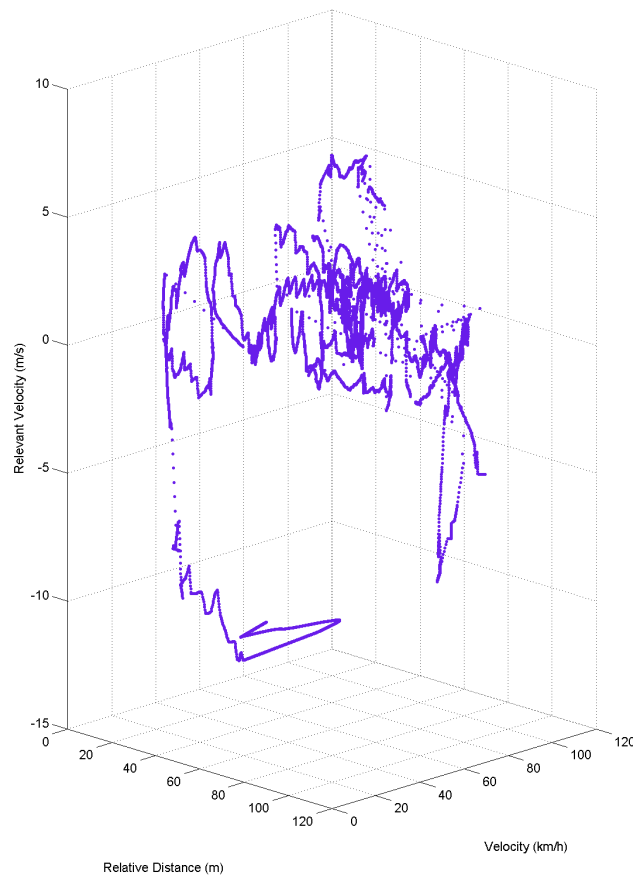
Figure 3.19: Velocity in relation with relative distance and relative velocity on October, 23rd in the morning with normal driving.

For the experiment with the ACC only vehicle signals were recorded while for the other two tests both vehicle signals and camera data are available.

In general, it is shown that the recorded data could clearly demonstrate the situation in the road. The data sets that contained errors or could not be matched with the camera data are discarded and are not used in the parameter estimation procedure. However, the amount of data that are analyzed and found reliable, is quite extensive and could be used for the further research objectives.

For the tests with the ACC and the normal driver it is shown that the driver is able to keep a constant car-following driving which resembles the driving with the ACC. However the driver cannot keep a constant relative distance and approaches the lead vehicle very often. With the use of the ACC the driving does not change and it is not influenced from exogenous factors and thus no actions points are expected. From the other hand,

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the driver seems to be influenced from some changes in the driving environment and an action point is expected.

In the extreme driving experiment, the ego vehicle changed its behavior continuously. A large variation in its movement is presented due to the continuous changes in its driving style and a lot of action points should be identified (not necessarily related with changes in the driving environment). The car-following task is not successful when the ego car does not have a constant behavior but as soon as it starts to have a more constant behavior behind the lead vehicle, the car following task is clear and action points can be observed when changes in the driving environment occur.

In the testing with normal driving, the changes of the lead vehicle (because of changes of lanes) create large variations in the data. The same variation is observed in secondary roads when the lead vehicle appears or disappears in side roads. This variation in the data (especially in the relative velocity and the relative distance) might have an influence in the estimation model since those data are used as input in the proposed system.

Chapter 4

Research Methodology

The methodology that is chosen for the identification of the driving behavior is the estimation of the parameters of a car-following model. The change of parameters reflects a change in the driving style and hence it shows the action points (thresholds) where the behavior changes (change from one set of parameters to another). The most important challenges in the research methodology are the selection of a car-following model, the selection of the most appropriate optimization method, the construction of the objective function and the development of techniques that offer a better result. All these challenges are discussed in this chapter.

4.1 Selection of the car-following model

For the driving behavior identification, two models are selected: the Helly model and the IDM (Intelligent Driver Model). Both models are already used in traffic systems since they offer a good representation of the car-following task, they are quite simple, they show better performance and are able to achieve a better fitting in data. However, in this thesis only the Helly model is used. In the beginning, both models were tested with the available data, but the IDM failed most of the times to match the observed with the calculated values. The reason was that there were a lot of assumptions that had to be made in the use of the IDM that would imply specific conditions in the road. Thus, the driving identification would succeed under a defined framework and not in a natural car-following situation. Furthermore, some of the parameters in the IDM do not make a sense from a behavioral point of view [25]. For example, while the velocity of the vehicle decreases, the free speed increases (not realistic). In contrast, the Helly model is simpler than the IDM and can be easily applied in a variety of car-following situations with good fitting results.

The Helly model is presented in the Equations 2.1 and 2.2. In these equations, the reaction time is included. However, in this research, the reaction time is not considered because the reaction time is difficult to assess and it can be compensated by the anticipation [74].

The reaction time includes the time needed for the driver to react and the delay due to vehicle dynamics. In normal driving conditions, drivers anticipate quite correctly what would happen during the next couple of seconds, and therefore do not need to react in the classical sense of being surprised and need some time to cope with a new un-anticipated event. Furthermore, in microscopic traffic simulation, the driver and vehicle are normally modeled as an integrated unit and the delay within the mechanical system of the vehicle is often neglected [43]. Equation 4.1 describes the model that is used in this thesis:

$$a_{calc} = \alpha \Delta v + \gamma (\Delta x - s_0 - h_{min} v) \tag{4.1}$$

All the data that are used in the above equation are instantaneous. The data that are used in the driving identification procedure are: the longitudinal velocity v, the relative distance Δx, the relative velocity Δv, the steering and the longitudinal acceleration a_{calc}. The steering is not used in the Helly model but it is used later in the analysis of the estimation results to observe where the vehicle change lanes or roads. Also, the steering is used in the parameter estimation model to separate the sections where the driver changes lanes. Furthermore, the longitudinal acceleration a_o is used in the objective function of the optimization method. The estimation of the parameters is done in relation with the driving time of the vehicle and not with the driving distance. The reason behind this choice is the easier matching of the estimation results with the camera data.

The parameters in the Helly model that are estimated are: the sensitivity of relative speed α, the sensitivity of distance differences γ, the minimum stopping distance s_0 and the minimum headway h_{min}. Some values for the parameters are added in the optimization procedure in order to save time and not start the estimation from the beginning. These values come from literature (there are common values used for the Helly model) and are presented in Table 4.1. Also, the minimum and maximum values of these parameters are presented there and are needed in the optimization procedure as bottom and upper boundaries respectively. The parameter α takes much higher values than the parameter γ (sensitivity of distance differences) and thus, the relative velocity is expected to have a larger influence on the calculated acceleration. The minimum stopping distance s_0 and the minimum headway h_{min} are expected to have a small influence on the calculated acceleration since they are multiplied by the parameter γ. Specifically, the minimum stopping distance is expected to have the smaller influence since it is not directly related to any of the variables (in contrast with the minimum headway which is related to the longitudinal velocity).

Another comment regarding the car-following model is the use of a multi-anticipative Helly model. In car-following behavior drivers anticipate future flow conditions by considering vehicles driving in front of their direct leader in the same lane. Multi-anticipative models show a better performance when used to analyze traffic flow phenomena (macroscopic) and thus researchers [51] recommend their use in microscopic analysis. However,

Table 4.1: Initial, minimum and maximum values for the parameters of the Helly model.

Parameters	Initial Values	Min	Max
α (sec^{-1})	0.2	0.1	1
γ (sec^{-2})	0.02	0.01	0.5
h_{min} (sec)	1	0	5
s_0 (m)	8	0	15

in this thesis, only the vehicle-based signals of the direct lead vehicle were available and thus the multi-anticipative Helly model is not used. According to Ossen [51] the use of multi-anticipative models increases the complexity of the traffic flow models. Furthermore, her research showed that the direct leader plays the most significant role in the actual execution of the car-following task by the follower. With the proposed model, it is shown (in the next chapter) that the representation of the car-following task is very successful by considering only one leader ahead. The main problem with the proposed model is when there is no lead vehicle in front, but the consideration of multiple leaders ahead would not solve this problem.

4.2   The objective function

The Helly model produces the longitudinal acceleration of the vehicle a_{calc}. From the vehicle-based signals the observed acceleration a_{obs} is known. The optimization is 100% successful when the calculations match the observations, in other words when the calculated acceleration is equal to the observed acceleration. The objective function that is used in this thesis is the Root-Mean-Square Error (RMSE). The RMSE is a frequently used measure of the differences between values predicted by a model or an estimator and the values actually observed. Basically, it represents the sample standard deviation of the differences between predicted and observed values. This measure serves to aggregate the magnitudes of the errors in predictions for various times into a single measure of predictive power.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(a_{calc_i} - a_{obs_i})^2}{n}} \tag{4.2}$$

The a_{calc_i} is the calculated acceleration and a_{obs_i} is the observed acceleration for every incoming data (i). The n represents the total number of incoming data. The optimization procedure tries to find the optimum value that minimizes the objective function. In other words, the system is searching for the parameters of the Helly model (Equation 4.1) that would minimize the error between the observed and the calculated acceleration (Equation 4.2).

4.3 Selection of the optimization method

The parameter estimation is made through an optimization procedure in which the parameter values of the car-following model are calculated based on a constant set of parameters in each cycle. For the optimization procedure different tools have been tested. The genetic algorithm is finally selected as it can offer better results (closer to reality) with its ability to approach the best solution in every generation of solutions. The genetic algorithms are robust search techniques formulated on the mechanics of natural selection and natural genetics. In few words, they start with a random population of solution chromosomes. The fitness function (objective function) is evaluated for each solution chromosome and the Darwinian law of natural evolution is simulated iteratively: the best chromosomes survive and a random part of them exchange or mutate the genes through the crossover and mutation procedure to produce more advanced offspring (Figure 4.1).

Crossover is a process of taking more than one parent solutions and producing a child solution from them. It is analogous to reproduction and biological crossover, upon which genetic algorithms are based. There are different methods for selection of the parent solutions. In the proposed system, the crossover method that is used is the arithmetic method. This method creates children that are the weighted arithmetic mean of two parents. The crossover operator linearly combines two parent chromosome vectors to produce two new offspring according to the following equations:

$$Offspring_1 = a \cdot Parent_1 + (1 - a) \cdot Parent_2 \tag{4.3}$$

$$Offspring_2 = (1 - a) \cdot Parent_1 + a \cdot Parent_2 \tag{4.4}$$

where a is a random weighting factor (chosen before each crossover operation). The crossover arithmetic method was selected after testing different methods since it produced better results (better fitting).

Mutation is a genetic operator used to maintain genetic diversity from one generation of a population of genetic algorithm solutions to the next. In mutation, the solution may change entirely from the previous solution. Hence genetic algorithms can come to a better solution by using mutation. Mutation occurs during evolution according to a user-definable mutation probability. This probability should be set low. If it is set too high, the search will turn into a primitive random search. The purpose of mutation is preserving and introducing diversity. Mutation should allow the algorithm to avoid local minimum by preventing the population of solutions from becoming too similar to each other, thus slowing or even stopping evolution. The general function of the mutation and crossover procedures are presented in a simple diagram in Figure 4.2.
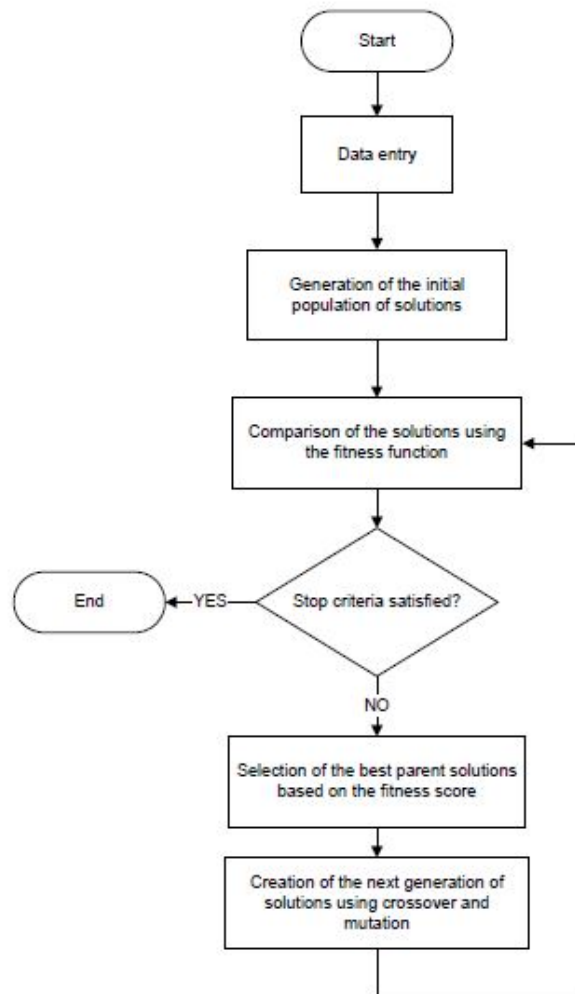
Figure 4.1: Basic function of the genetic algorithm [53].
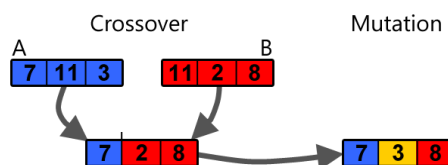
Figure 4.2: The general function of the crossover and mutation procedure of genetic algorithms.

The mutation method that is used in the proposed system is the Gaussian. This method adds a random number taken from a Gaussian distribution with mean 0 to each entry of the parent vector. The standard deviation of this distribution is determined by the parameters *Scale* and *Shrink*. The *Scale* parameter determines the standard deviation at the first generation. The *Shrink* parameter controls how the standard deviation shrinks as generations go by. If you set *Shrink* to 1, the algorithm shrinks the standard deviation

Table 4.2: Selected options for the genetic algorithm.

Options	Values
Max Number of Generations	1000
Stall Generations Limit	1000
Fitness limit	0
Limits and Initial values	Table 4.1
Mutation	Gaussian
Crossover	Arithmetic

in each coordinate linearly until it reaches 0 at the last generation. A negative value of *Shrink* causes the standard deviation to grow. The mutation method used in the system is the default method in the Matlab code and after some testing it was found that no other method produced better results. Thus, for simplicity of the code, the default method is finally selected. The default value[1] of both *Scale* and *Shrink* is 1.

Another option of the genetic algorithm that has to be selected is the stopping criterion. In the proposed system one stopping criterion is used: the maximum number of generations. However, Matlab has some default values for other existing stopping criteria. If those criteria stay unchanged, the selected stopping criterion cannot be applied because the rest of the stopping criteria reach their default values. These criteria are the fitness limit and the stall generations. The algorithm stops if the best fitness value is less than or equal to the value of the fitness limit. With the stall limit criterion, the algorithm stops if there is no improvement in the objective function for a sequence of consecutive generations of length equal to the stall generations value. The stall limit criterion is selecting to be the same as the maximum number of generations so that the genetic algorithm executes the requested number of generations even if no improvement is presented in the fitness function. The fitness limit is set to 0 since the desired outcome is zero difference between the calculated and the observed accelerations (Equation 4.2). Another option would be to set the fitness limit very low (e.g. 10^{-6}) and enable the genetic algorithm to stop if this fitness limit is observed. This may save computational time without considerable differences in the results. This option is not included in the system (due to oversight), but it is highly recommended for future study. All the choices that are made for the genetic algorithm are summarized in Table 4.2.

The genetic algorithms do not require differentiability, convexity or other auxiliary properties of the problem parameters. The only drawback of the genetic algorithms is that they do not guarantee global optimum solutions, but if properly designed, they can often provide either optimum or near optimum solutions to the model. In contrast with other optimization tools, they have more chances to avoid a local optimum due to the mutation characteristic.

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[1]More   information   about   the   Gaussian   mutation   operator   can   be   found   in: http://www.mathworks.nl/help/gads/genetic-algorithm-options.html

Another drawback of the genetic algorithm is observed if the system has to estimate the parameters in a car-following model in real-time. The genetic algorithm takes much time to run a series of generations defined by the user. The fewer the generations, the less time is needed for estimation, but the worse the results that are produced. Hence, it is required for the genetic algorithm to run a long time to give reliable results. For that reason another tool is also tested which finds a minimum of unconstrained multivariable function using a derivative-free method. The tool searches for the minimum of a scalar function of several variables, starting at an initial estimate. This is generally referred to as unconstrained nonlinear optimization. This tool gives constant, good results in less than a minute but the results are less accurate than those of the genetic algorithm. In Chapter 5, the results from both methods are presented and are analyzed.

4.4   Model development

In order to estimate the parameters of the car-following model a moving estimation window has to be chosen, in other words the number of data that can be used in every estimation cycle. After different tests, it was observed that an average number of about 180 seconds of driving is appropriate for an estimation cycle. There are two main reasons behind this choice. First of all, a visual representation of the identification is needed. This can be done by plotting the observed and the calculated accelerations from the car-following model. If the time length of the estimation window is larger than 180 seconds, no visual representation is possible (too many data output points in each graph). The visual representation of the action points is necessary in order to compare the results with the camera data and determine the main reasons for changes in the driving style.

Furthermore, in the estimation procedure a constant set of parameters is used for the each estimation cycle. If the time length of the estimation cycle is larger than 180 seconds, the constant set of parameters cannot offer a good fit anymore due to changes in the driving style. From the testing of the system, it is found that that statistically the driving style changed in less than 3 minutes and a constant set of parameters cannot be applied if the data have a very high variability (large variations due to changes in the driving style). From the other hand, the moving estimation window should not be too small, because the estimation procedure cannot offer reliable results (not enough data to execute the optimization and succeed a good fitting result). Hence, the estimation window should be at least 60 seconds.

The choice of 180 seconds as the cycle time does not necessarily mean that the driving style changes every 180 seconds. In the next cycle it is possible to have the same set of constant parameters if the driving style is unchanged. The moving estimation window is only used as a tool to facilitate the estimation procedure. The action points are identified only where the constant set of parameters is not able to offer a goof fit in the data, as it would be explained in the next section. Moreover, the value of the estimation window is selected

in the beginning of the system and can be easily changed based on the interest of the user.

Instead of assuming a constant set of parameters for a time period (for 180 seconds), the identification of the driving behavior every second was also tested. If the identification of the driving behavior is made every second, a different set of parameters is estimated (for every second). The total identified set of parameters was analyzed in the end and the result did not make any sense. In other words the set of parameters changed so much in every second that no conclusion could result from the analysis. A similar estimation procedure was used from Hoogendoorn [24] in the driving identification under adverse and emergency conditions and the parameters presented a high variation throughout time. The reason for this is that different sets of parameters can fit the equation almost equally well. However, when a constant set of parameters is asked for the whole time period a choice is made for the set of parameters that offers better fitting results for the whole time period.

The system that is used for the parameter estimation is written in Matlab. The procedure is described below and is summarized in Figure 4.3. Also, a visual representation of the proposed methodology is presented in Figure 4.4. In the Appendix, there are detailed flow charts of the model and some extracts of the Matlab code.

- The data are loaded: relative velocity, relative acceleration, longitudinal velocity, longitudinal acceleration and steering.

- The estimation window is chosen. In this project, the estimation window is 3 minutes (180 seconds or 18000 data points).

- The accuracy level of the estimation is selected. The accuracy level is used in the next steps to decide if the estimation is good or further estimation is needed. In this thesis, different levels of accuracy are tested.

- The optimization procedure is executed and a table is created with the set of the parameters.

- The accuracy level is checked for every data point in the step. If the accuracy is not good, a second optimization is executed only for the problematic parts.

- The table is updated with the new parameters.

- The calculated and the observed acceleration are plotted and the results are saved.

$$A_i = |a_{calc_i} - a_{obs_i}| \tag{4.5}$$

The accuracy of the estimation (A_i) is calculated from Equation 4.5 for each data point in the step (moving estimation window). The accuracy calculates the difference of the
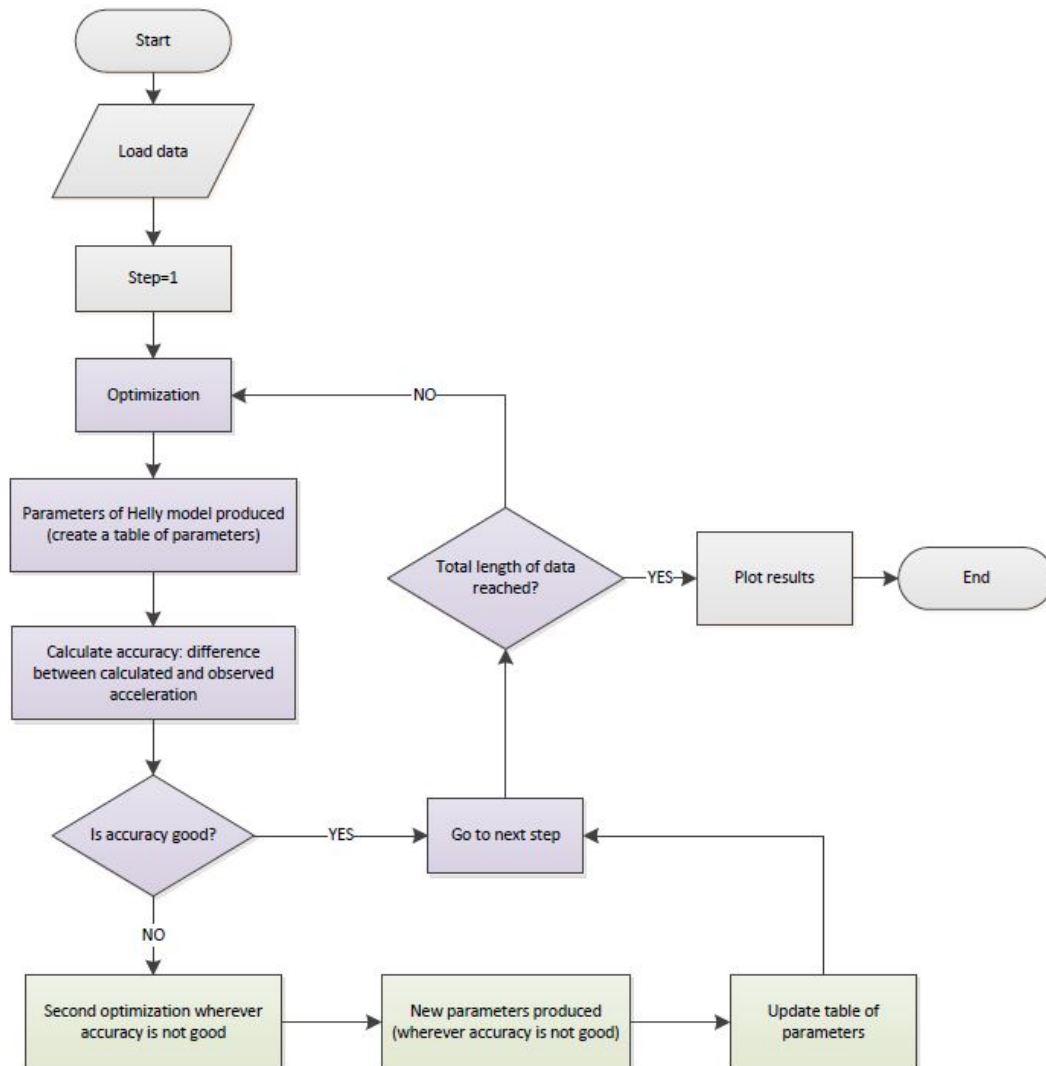
Figure 4.3: General flow chart of the proposed system.

accelerations with the estimated parameters and then the difference is compared with the desired difference of accelerations (e.g. 0.1 m/s^2) based on the choices of the user of the system.

Then, the number of continuous data points with "bad" accuracy are calculated. If the length of these data points is greater than a threshold (the length of the problematic part), the second estimation takes place. If the length is smaller than a threshold, then the second estimation is not done (the data points are not considered as a problematic part). In this project, the threshold is selected to be 20 seconds (2000 data points), as it was found that in less than 20 seconds a new driving style cannot be applied to the driver. In other words, 20 seconds at least are needed for a new driving style to be
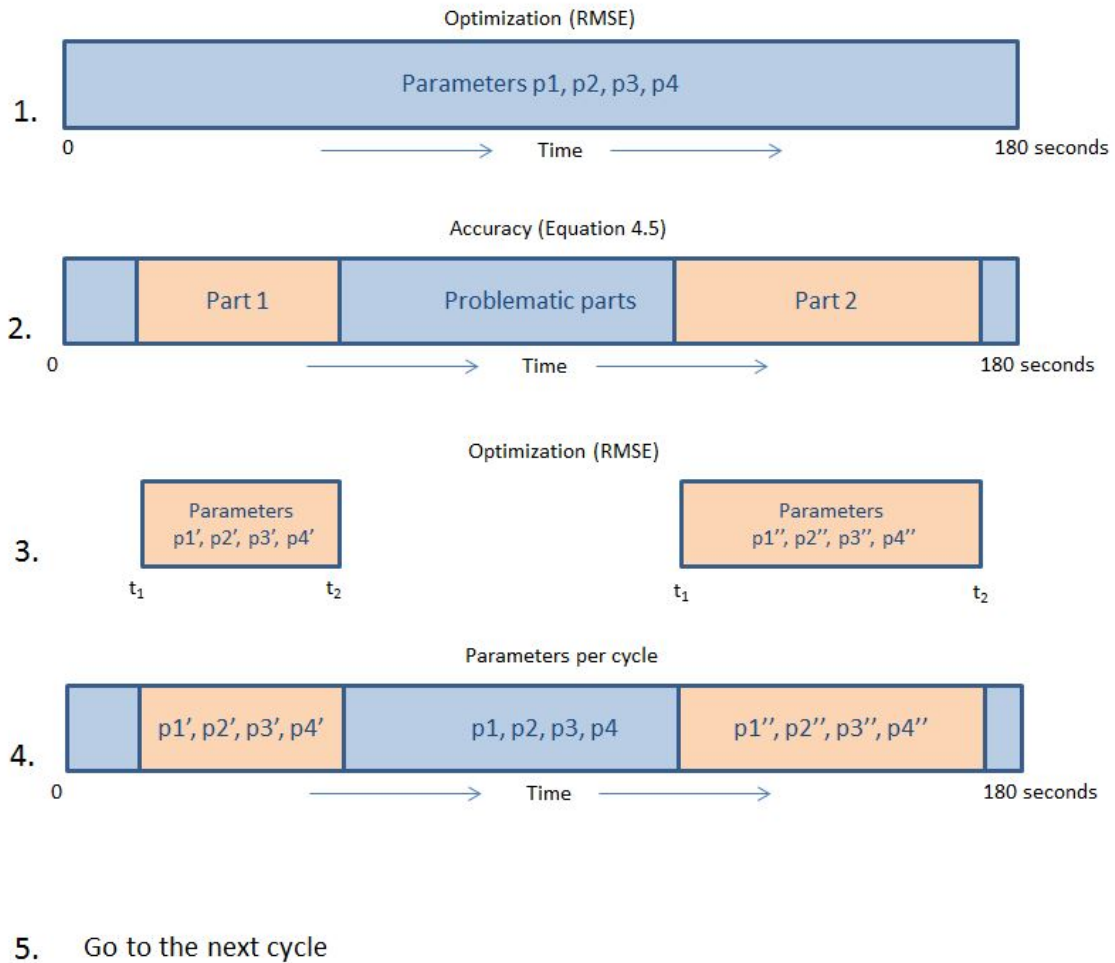
Figure 4.4: Schematic representation of the proposed methodology.

considered. The cause for this may be that the driver needs some time to get used to the new situation (for example after the change of a lane) and start having a constant behavior. The system needs at least some seconds of constant behavior in order to find a set of parameters (constant) that produces a good fit with the actual driving behavior. In addition, if different sets of data points with "bad" accuracy and length higher than the threshold are found, the length of the data points with "good" accuracy that exist between the "bad" data sets is checked. If the length of those "good" data point is smaller than 4 seconds (400 data points), then the two "bad" data sets are considered as one larger data set including the good points. This is done because it is unlikely for the driver to return to his previous driving style for less than 4 seconds and the good accuracy may have occurred by coincidence. The selection procedure of the problematic parts that need a second estimation is described in Figure 4.5 and even more accurately in Figure A.2.

Before the second estimation, a set of criteria is checked for the problematic parts in order
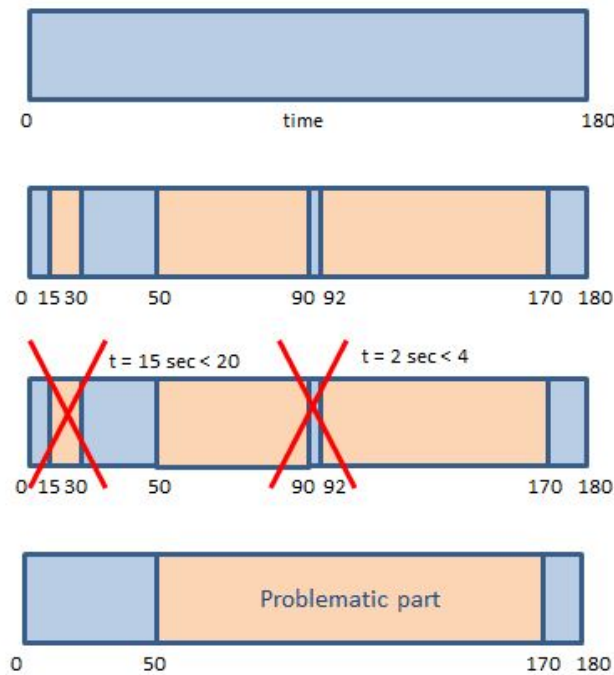
Figure 4.5: Schematic representation of the selection procedure for the problematic parts.

to save time by recognizing some changes in the driving environment directly from the data. The criteria were formed after data and camera analysis, where it was observed that the Helly model could not identify the driver's behavior under some circumstances. The first criterion is the existence of a car in front which is a presupposition for the car-following task. This criterion is fulfilled if the relative distance is smaller than 100 meters. The second criterion is the normal behavior of the car, which means not a continuous changing of lanes and not extreme acceleration and deceleration of the car. This criterion is fulfilled if the difference between the higher and the smaller value of the steering data in the problematic part is less than 5° and if the difference between the higher and the smaller value of the acceleration values in the problematic part is less than 5 m/s². If the criteria are not fulfilled, then the system displays the message that no identification is possible in that part and gives the value zero to the calculated acceleration and to all the parameters in that part.

Another option that has to be selected before the second estimation is made, is the initial set of parameters. The system uses the initial given set of parameters in the first step of the estimation (Table 4.1). Then, the initial set of parameters is replaced by the last estimated set of parameters since it is assumed that doing so, the procedure would start from a point closer to the optimal solution and some searching time would be saved. However, in one data set it is also tested whether the use of the initial set of parameters in every step offers better results and the results are presented and discussed in Chapter 5.

Table 4.3: Selected options for the proposed system.

Options	Selection
Estimation window	180 sec (3 minutes)
Min time length for different driving style	20 sec
Max time length to consider one driving style	4 sec
Criterion: No car-following situation	RelDist > 100
Criterion: Steering	Difference in steering $> 5°$
Criterion: No extreme driving	Difference in acceleration > 5 m/s^2
Repetitions of GA	30
Accuracy level	0.1, 0.3, 0.6, 0.9 m/s^2

The genetic algorithm, as explained before, can be captured in local optimums. In order to avoid such problem, the optimization procedure should be repeated many times from the beginning. Statistically, the more times the genetic algorithm runs, the more possibilities exist to get closer to the best solution.

All the options that are selected for the proposed system, are summarized in Table 4.3.

After the estimation of the parameters is presented, the results can be analyzed to find the action points. There are two possible scenarios to detect the action points:

- The beginning of the problematic parts. There, a second optimization takes place and a new set of parameters is determined (different driving style). The driver reacts with something in the driving environment and changes completely his driving style.

- From the visualization of the results, the points where the calculated and the observed acceleration do not match. In those points, a second optimization procedure is not offered because of the limited length of the data points with "bad" accuracy. A change in the driving environment has occurred, but the duration is not long enough for the estimation of the driving style. For example, the driver changes lanes and in the next lane he finds similar conditions as in the previous lane and returns to his previous driving style. For the small time period that the driver changes lanes, no identification is possible, but still this is an action point.

In the end, the proposed system calculates the overall accuracy of the model. This is done by using the Equation 4.5 and by calculating the accelerations with the updated table of parameters (if a second estimation is performed). The number of data points with the desired accuracy divided by the total number of data points gives the performance of the model.

4.5   Summary

In this chapter the proposed research methodology is described. First of all, a car-following model is selected. From the state-of-the-art review the Helly model and the IDM are the most appropriate to be used in a parameter estimation approach from vehicle-based signals. The Helly model is simpler than the IDM and its changes in the parameters can be explained from changes in the vehicle-based signals while the changes in the parameters of the IDM cannot always be explained. The Helly model parameters that have to be estimated are the sensitivity of relative velocity, the sensitivity of distance differences, the minimum stopping distance and the minimum headway.

The objective function is the root mean square error which minimizes the differences between the calculated acceleration from the Helly model and the observed acceleration from the data. Two different optimization methods are tested, the genetic algorithm and the unconstrained nonlinear optimization. The genetic algorithm is selected since it can get closer to the optimum solution while the unconstrained nonlinear optimization is selected as a time saving method.

In the proposed methodology, the optimization tool calculates the parameters of the Helly model by using a moving estimation window. Then, with the estimated parameters the acceleration is calculated and it is compared with the observed acceleration of the vehicle. Based on the difference of the accelerations and the choices made in the proposed system, the problematic parts are identified. In these parts a second optimization takes place and different sets of parameters are produced. The action points are the points where the problematic parts begin and end. Their relationship with the driving factors is investigated in Chapter 5 after the analysis of the results of the parameter estimation procedure.

Chapter 5

Outcome of the parameter estimation model

The identification of the driving behavior is performed through an optimization procedure which searches for the optimum set of parameters of the Helly car-following model. The optimum set of parameters minimizes the difference between the calculated acceleration from the Helly model and the observed acceleration from the vehicle-based signals. The basic function of the estimation model is described in Chapter 4. The results of the parameters' estimation procedure are presented in this chapter. First, some data sets are selected and their results (accelerations and optimum parameters) are analyzed. Then, a table is constructed which summarizes all the observations from the analysis of the results. The next step consists of a performance analysis of all the results and an evaluation of the estimation model. In the end, all the tools and the options that are tested are evaluated on their capability to be used in a real-time application.

5.1 Presentation and analysis of the results

In the data collection process, three different tests were conducted: the extreme driving, the use of the ACC system and the normal driving. All the data that were collected are tested with the parameter estimation model. In this chapter, only two data sets from each test are selected and are further analyzed. The selected data sets are the same that are presented in Chapter 3 since the data analysis indicates the conditions on the road and the expected behavior of the driver. Thus, for those data sets a comprehensive research is presented throughout the whole report. The calculated and the observed accelerations are presented in plots where also the relative distance, the relative velocity, the longitudinal velocity and the steering are shown. By observing the performance of the other signals it is easier to come to conclusions regarding the differences between the accelerations. All the other data sets that are analyzed can be found in Appendix B with some comments on the presented results.
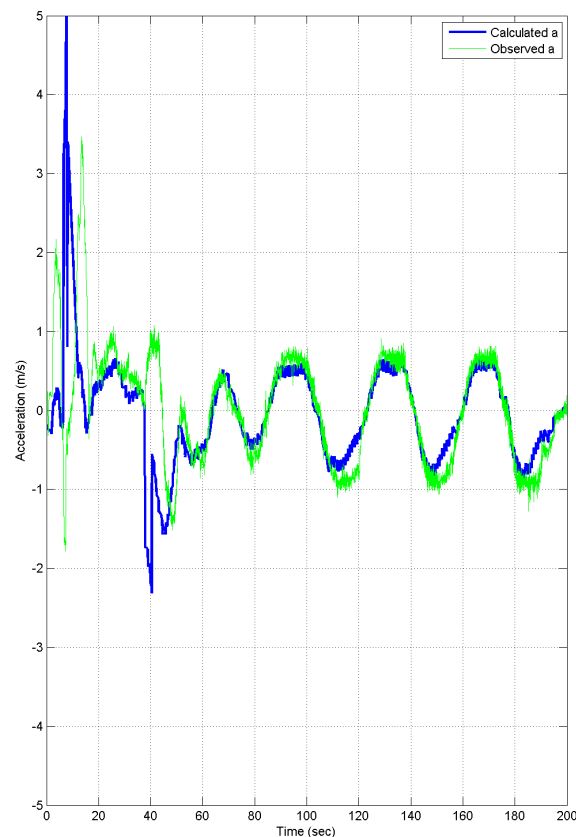
Figure 5.1: Observed and calculated acceleration of data set 7 (ACC) of the experiment with ACC on October 15th.

5.1.1   Car-following with ACC

The first experiment with the ACC system and the driver is used as a performance in-dicator of the proposed model. In other words, the data sets from this experiment have been used in the construction of the model. The ACC produced a constant behavior and the system was calibrated so that it could reproduce that behavior. Unfortunately, no video was recorded with this experiment and no in-depth analysis of the results is now possible.

Only the last two data sets (Table 3.3) of the experiment with the ACC are used in the estimation procedure, since they are the most appropriate for the comparison between the use of ACC and the driving behavior (same conditions on the road). In data set 7, the ACC was used and the lead car was asked to have a variable speed between 80 and 120 km/h. The total length of this data set is 200 seconds. The parameter estimation proved successful in this data set as it can be seen from Figure 5.1. Since the ACC keeps a
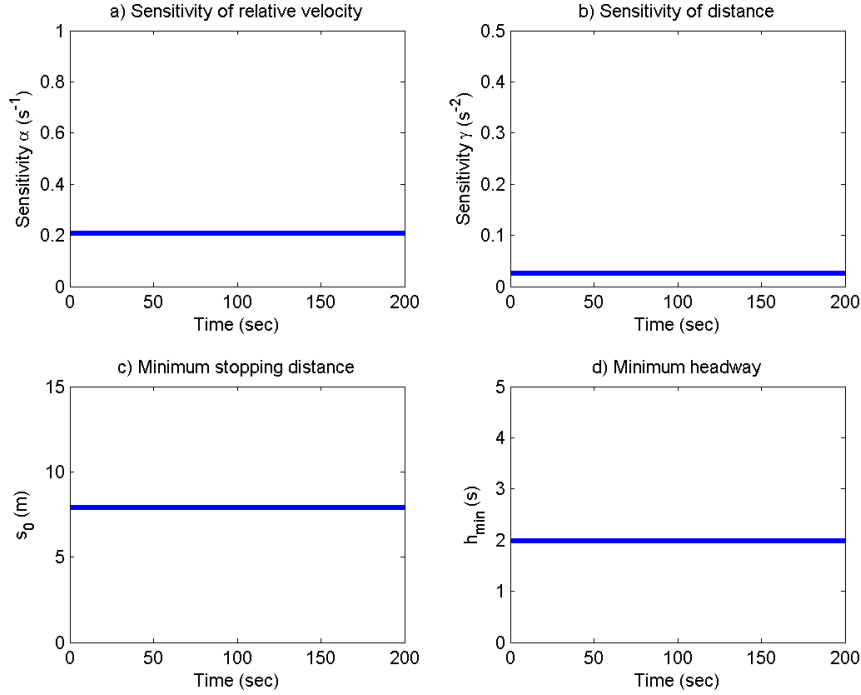
Figure 5.2: Parameters and estimated action points of data set 7 (ACC) of the experiment with ACC on October 15th.

constant behavior the whole time, no action point is identified (as expected and stated in Chapter 3). This can be observed from Figure 5.2 where one set of parameters is selected by the model for the whole time period (straight line without steps).

The data that were selected with the ACC offer the best fitting between the observed and the calculated accelerations. This can be explained from the equation of the Helly model (2.1). The calculated acceleration depends strongly on the relative velocity. With the ACC, the relative velocity has a uniform distribution around 0, so the car-following task is achieved with high precision and the acceleration can be correctly identified. Another reason for the good fitting is the large possibility that the ACC uses the Helly car-following model. The most widely reported ACC model is a proportional derivative controller, where the vehicle acceleration is proportional to the gap (net distance headway) and relative speed with respect to the preceding vehicle (derivative of gap) at car-following conditions. This controller is essentially a Helly car-following model [75].

In data set 8, the driver had the full control of the ego car and the lead car was asked to have a variable speed between 80 and 120 km/h. The total length of this data set is 250 seconds. The parameter estimation proved quite successful in this data set as it can be seen from Figure 5.3, although the lead car had a continues change in its movement (variable speed). The model is able to identify two action points (Figure 5.4). This was
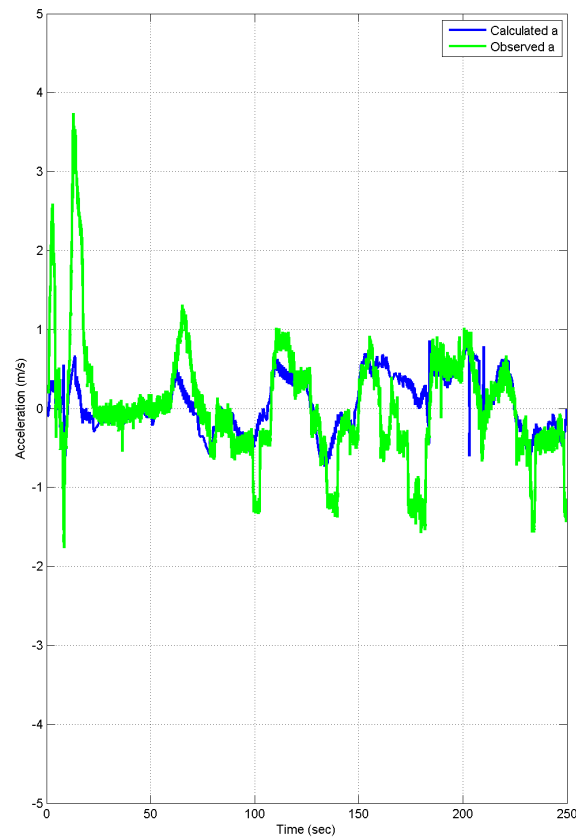
Figure 5.3: Observed and calculated acceleration of data set 8 (Driver) of the experiment with ACC on October 15th.

expected after the data analysis since two spirals were observed in the relative speed-relative velocity plane (Figure 3.9). From 180 until 210 seconds the driver seems to adopt another driving style. Despite the fact that a different set of parameters is proposed for that section, the accelerations do not match and that offers the first clue for the limitations of the proposed model. By observing Figure 3.7, it can be seen that in that section the relative velocity and relative distance have very low values and after a while the relative distance turns to be higher than 100 meters. A logical explanation can be that the driver changed lane or turned to a secondary road and there was not a lead vehicle anymore in front of the ego car (and thus no car-following task). However, this can not be further verified since no video data are available.

The estimated parameters for both data sets are presented in Table 5.1. As it can be observed, the sensitivity of the relative velocity α and the sensitivity of distance differences γ have the same values in both data sets. That might be an indication that in normal car-following situations a specific set of parameters can be applied for the same driving
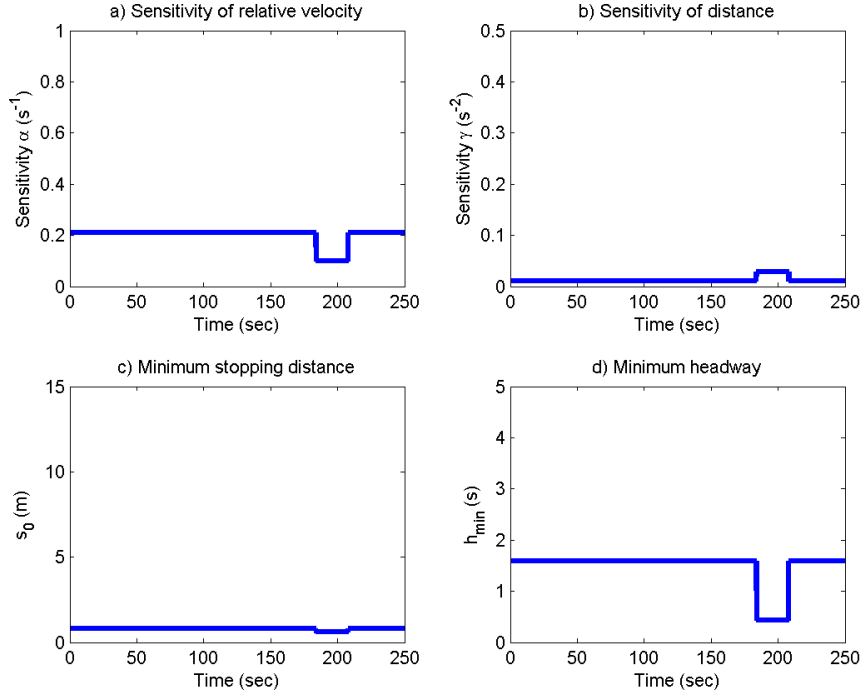
Figure 5.4: Parameters and estimated action points of data set 8 (Driver) of the experiment with ACC on October 15$^{\text{th}}$.

Table 5.1: Parameters in data set 7 (ACC) and 8 (Driver) of the experiment with ACC on October 15$^{\text{th}}$.

Parameters	ACC	Driver
α	0.23 s^{-1}	0.23 s^{-1}
γ	0.02 s^{-2}	0.02 s^{-2}
s_0	1.00 m	8.00 m
h_{min}	1.60 sec	2.10 sec

conditions (taking into consideration that the driver and the car are the same and the following task is similar). The minimum stopping distance and the minimum headway are different, but as it is mentioned in Chapter 4, those parameters are expected to have a small influence in the calculated acceleration.

From the first calibration, there is a positive feedback that the proposed identification method can succeed (since the behavior of the ACC is identified). However, from the data set with the driver there is a strong indication that the proposed system has some limitations. Without certainty, those limitations could be found in the steering, the movement of the lead car and the relative distance between the two cars. In order to overcome the uncertainty and correct the proposed system so that it can cover a larger area of conditions, further calibration is necessary.

5.1.2   Extreme car-following conditions

The test with the extreme car-following conditions is used for a further calibration procedure. After the analysis of the estimation results of this experiment, the proposed system was updated to its final form which is presented in Chapter 4. Two data sets are selected for this experiment, data set 1 and data set 13. The rest of the valid data sets are analyzed in Appendix B.

In data set 1, the ego car decelerates and accelerates continuously and without an obvious reason. The total length of this data set is 160 seconds. The parameter estimation does not completely prove successful in this data set as it can be seen in Figure 5.5. The driver of the ego car displays an extreme movement (deceleration) that the model does not expect (the Helly model). Based on the incoming data (relative velocity, relative distance), the model do not anticipate a large deceleration as it happens in reality. The parameter estimation system is not able to capture the sudden decelerations of the driver because of their sudden appearance and the limited time period that they last. The accelerations are better captured due to their larger time length. Furthermore, the driver starts to accelerate when the relative distance is quite high (in order not to have any accident) and due to this large value of the relative distance the acceleration is anticipated by the model.

From the video analysis, it is observed that at second 350 there is a moving block in front of the lead car (position n+2) which stays there for 40 seconds. Thus, none of the two experimental cars can accelerate anymore. From the second 390, the two cars prepare to stop in a traffic light and both change lane at the same time. The simultaneous change of lanes is important because it shows that the relative distance does not change when the follower car changes lane. When preparing to stop in the traffic light there is traffic and the driver decelerates due to decelerations of the other vehicles, but the Helly model (mostly based on the relative velocity) cannot identify that behavior.

The estimation is not totally successful, in other words there are data points that the accelerations differ more than the selected threshold of 0.1 m/s^2. However, the difference in the accelerations does not last more than 20 seconds and that is why it cannot be captured from the model as a different driving style. This results in one set of parameters (Figure 5.6) and no action points for that data set. It has to be noted here that the threshold of 20 seconds is selected in Chapter 4 as the minimum time period needed for a different driving style to be identified.

In data set 13, both cars are moving with high speeds (80-100 km/h). In the beginning, the lead car has a very large distance with the ego car (> 100 m) and the follower tries to decrease that distance. When it manages to get closer to the lead car, the ego car decelerates suddenly and from that moment (25 sec) it starts following the lead car. From that point the follower has a constant driving style. The total length of this data set is 160 seconds.
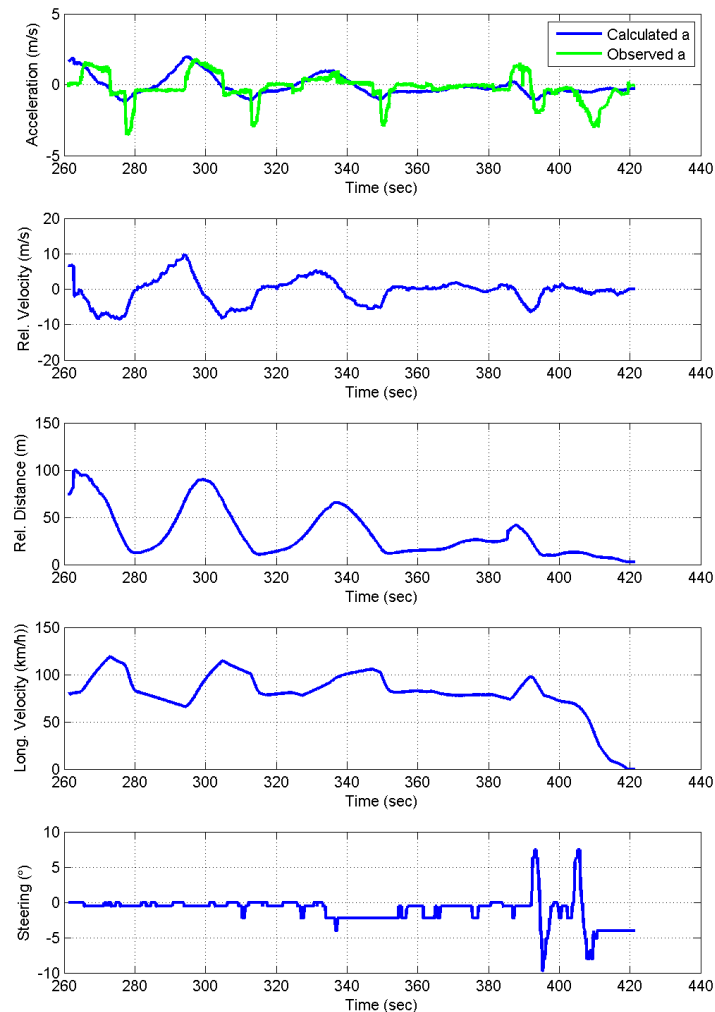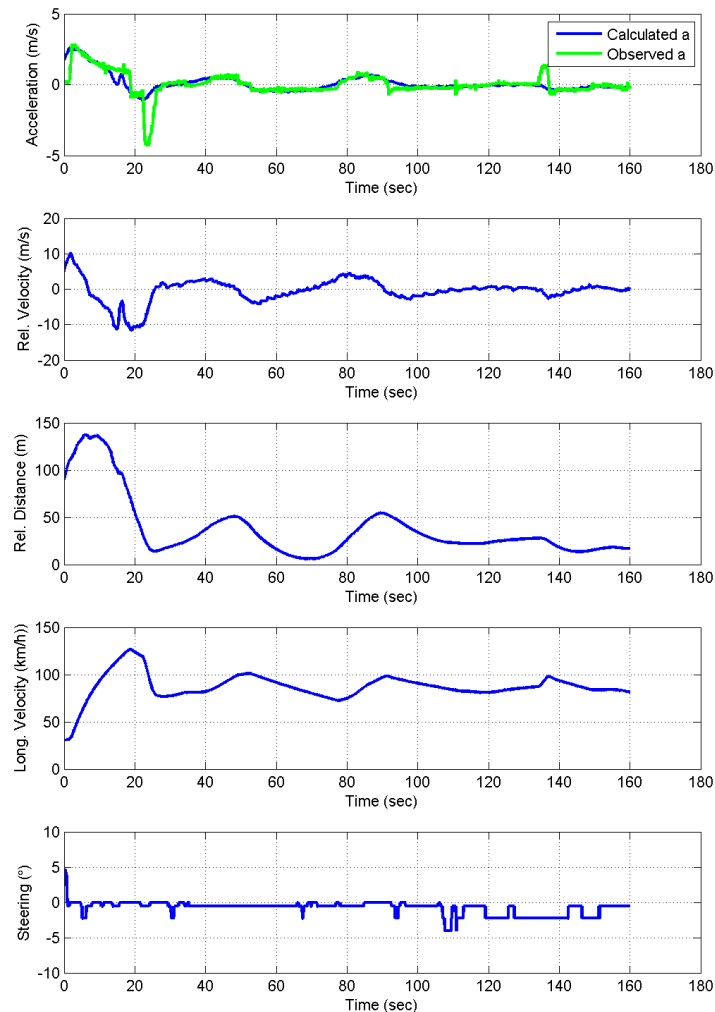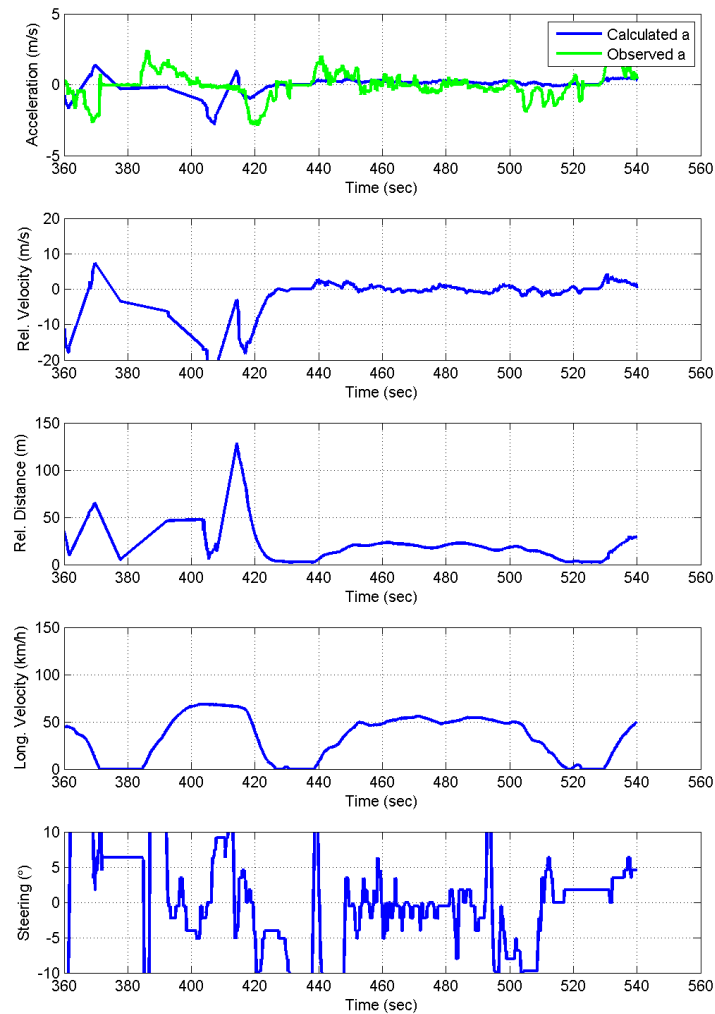
Figure 5.5: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points of data set 1 (extreme driving, October 3rd).

From Figure 5.7, it can be observed that the estimation is successful. This is possible since the driver kept a constant driving style and as a result no action points are found (Figure 5.8). At the 20 sec, a small mismatch is observed in the accelerations. This happens because the driver gets very close to the lead car and decelerates very suddenly. At the 135 sec, again the two cars get very close and the follower decelerates.

After the test with the extreme driving conditions three situations are determined where the estimation cannot be accurate. The relative distance with the lead car is very important since it defines the car-following task. If that distance is very high (> 100 meters)

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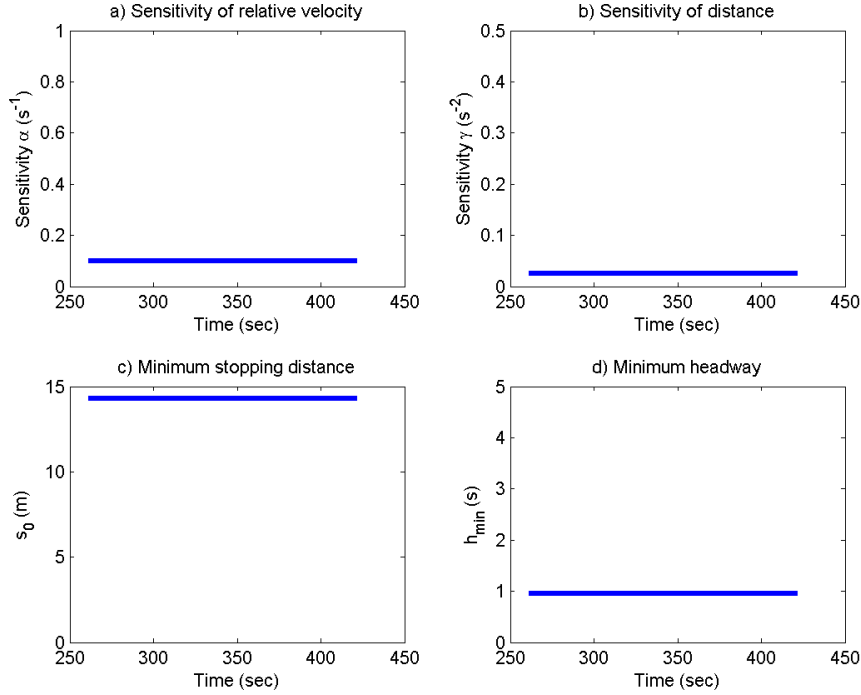
Figure 5.6: Parameters and estimated action points of data set 1 (extreme driving, October 3rd).

the estimation is not possible due to the definition of the Helly model. Furthermore, when the driver changes lanes, the relative distance with the lead car changes and this leads to bad estimation results. The change of lanes can be identified from the steering values. Another conclusion that is made with the extreme driving conditions, is the difficulty to perform the estimation in data from secondary roads due to the continuous change of the lead vehicle (in and from side roads). Finally, the car does not have the expected behavior when the relative distance with the lead car is low and the ego vehicle brakes suddenly.

5.1.3   Normal car-following conditions

From the first two tests, the proposed system is found to be reliable in most of the cases. Also, the conditions under which the estimation is not possible are reported. The third test is used to validate all the results that are made from the previous experiments. In the normal driving, there are large data sets of driving data and are analyzed in a moving window of 3 minutes. The first results that are presented come from the 22nd of October, in the evening.

Figure 5.9 shows the movement of the car from 360 sec (after 6 minutes of driving) until 540 sec. The estimation is not very good, especially in the first 60 seconds (until 420 sec). In that period large steering takes places and from the video analysis, it is found that the
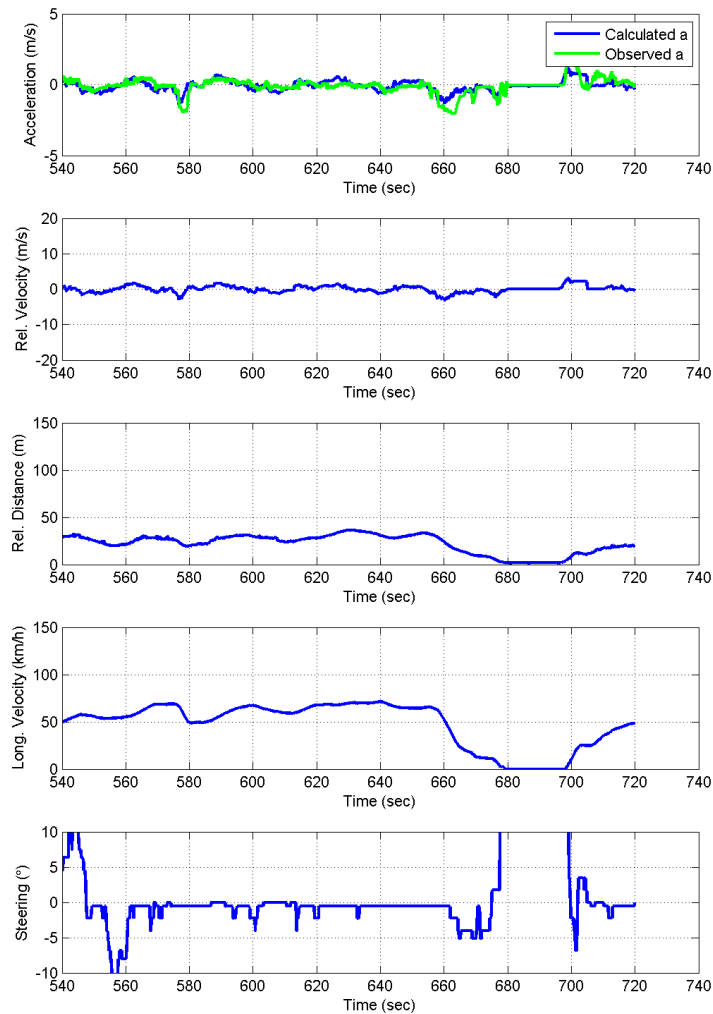
Figure 5.7: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points of data set 13 (extreme driving, October 3rd).

car is moving in a secondary road with not always a car in-front and with sharp curves (Figure 5.10). Then, the car continues in a secondary road with one lane per direction and sharp curves. It can be observed that the sharp curves which lead to large steering are conditions under which the estimation can not succeed with the proposed model.

The proposed system identifies a different set of parameters between 380-420 sec (Figure 5.11). The action point 380 is not valid since in that time period there is no car in-front and the estimation is wrong. However, the second action point at 420 sec is valid. The car enters a new secondary road and performs a car-following task. However, some other
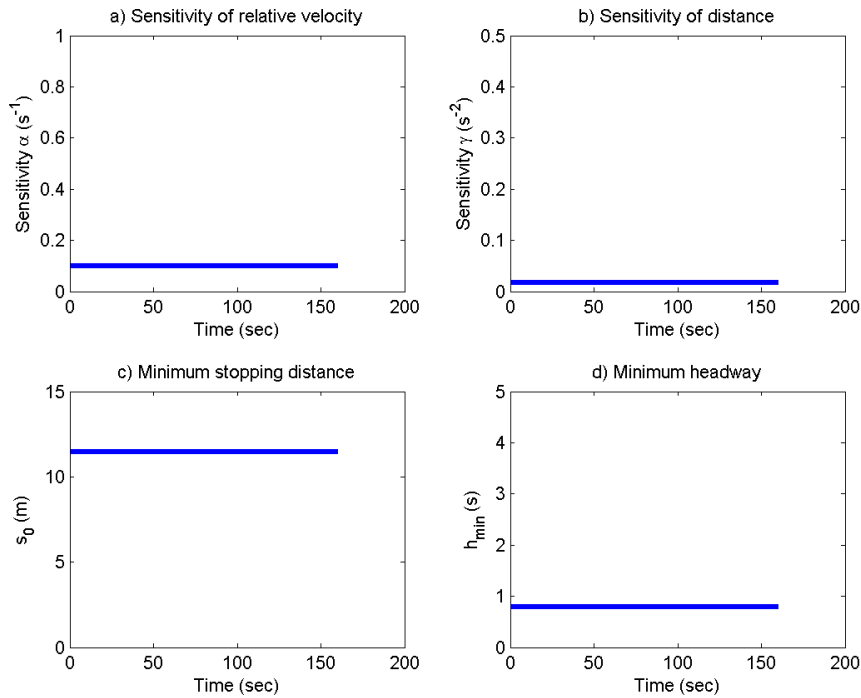
Figure 5.8: Parameters and estimated action points of data set 13 (extreme driving, October 3rd).

conditions (sharp curves and steering) create mismatchings between the accelerations.

From 540 sec until 720 sec, the car performs a simple car-following task. As it can be observed (Figure 5.12), the estimation is successful with one set of parameters (no action points) for the whole time period of 3 minutes (Figure 5.13). At 570 sec there is a small mismatch between the calculated and the observed accelerations. This is due to a small relative distance ($<$ 20 m) between the car and the lead vehicle and a sudden brake of the lead car (Figure 5.14). The same happens at 660 sec where the car stops in a traffic light and due to traffic is forced to decelerate when the lead car brakes (Figure 5.15). After the traffic light turns red, the traffic continues in the same direction as the examined car and as a results the driver is forced to change his driving style (very slow driving from that point).

On the 23rd October in the morning, it is still dark outside. The car moves in a highway but there are a lot of sharp curves and long time periods without a lead car (Figure 5.16). The continuous change of lanes of the driver, especially in the first two minutes, creates some mismatches between the accelerations (Figure 5.17). From the 1400 sec, an action point is identified (Figure 5.18), since the car finds a truck in-front (which moves with a normal speed, not moving block) and starts performing a car-following task.

At 1440 sec, the car changes lane and starts another car-following task with a passenger car (Figure 5.20). The new car-following task is not influenced from the composition of

Figure 5.9: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points on 22nd October (normal driving).

the traffic in the next lanes (e.g. trucks, Figure 5.19). The car keeps a constant relative velocity and relative distance with its lead vehicle even if there are some curves (not very sharp though) on the road. From the 1510 sec there are some small mismatches between the accelerations but this is mainly because the car changes lanes and some time is needed before the car-following task can be performed. This time is found to be around 4 seconds. It is quite interesting that even if the driver changes lanes, he is able to have the same driving style in the next lane, so no action points are observed (Figure 5.21).

Figure 5.10: Image of the camera data on 22$^{\text{nd}}$ October at 390 sec (normal driving).
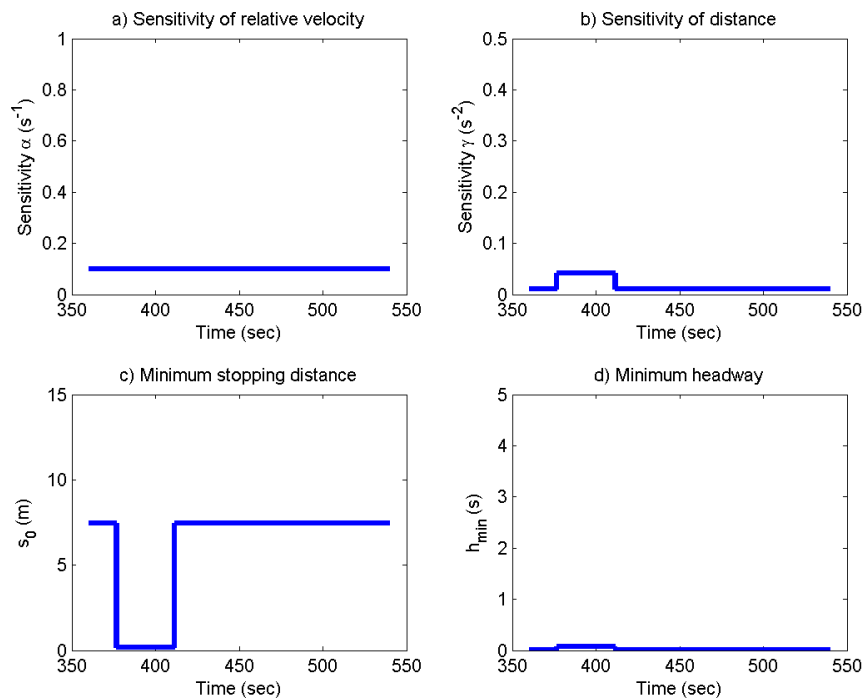
Figure 5.11: Parameters and estimated action points on 22$^{\text{nd}}$ October (normal driving).

5.2 Evaluation of the results

In the previous section some results are presented. With the proposed system all the available data have been analyzed. However, it turned out that there are some time periods where wrong data were obtained or no video data were recorded. Furthermore, the driver (in normal driving) stopped in car-parking and turned off the camera in some sections. As a result, it was impossible to match the camera data with the vehicle-based signals in those parts. Also, the morning signals were not very good because it was dark and the collected data were not so reliable. Hence, from the normal driving only 114
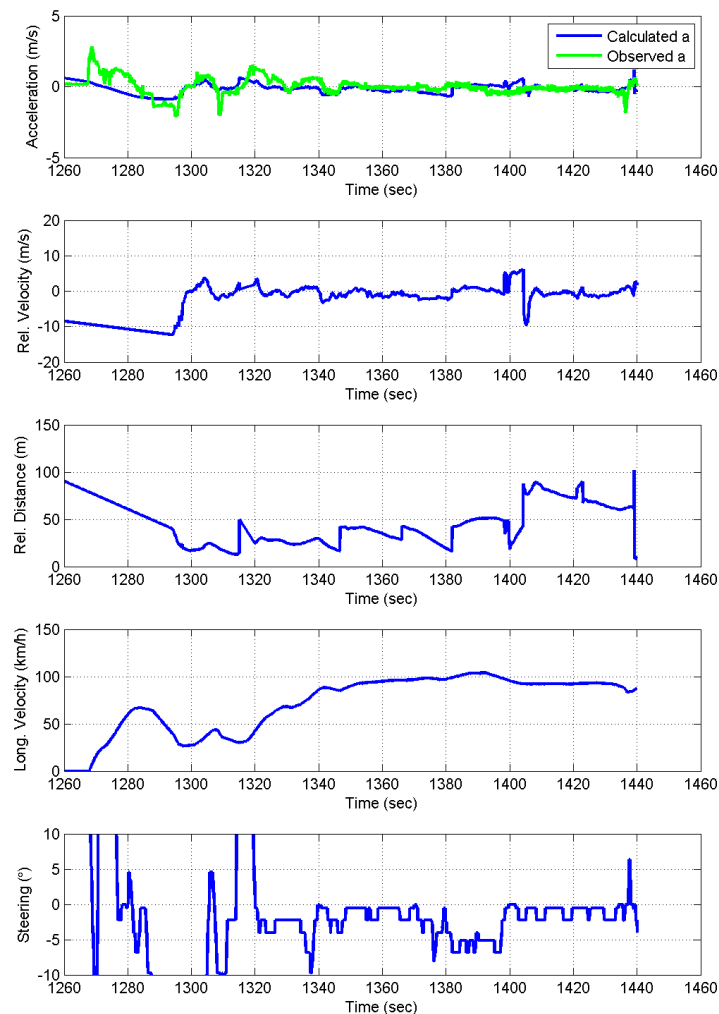
Figure 5.12: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points on 22nd October (normal driving).

minutes of driving have both camera data and vehicle signals and have been analyzed. From the test with the ACC, only two data sets have been analyzed and from the test with extreme driving, seven data sets are presented in this report (two data sets fully analyzed in Chapter 5 and five data sets in the Appendix).

After the analytical observation of all the results, more concrete conclusions are made of the circumstances under which the driving behavior can be estimated. First, a list is made for the conditions under which the proposed model cannot offer a good estimation (Table 5.2). This means that no matter how many times the estimation is repeated, those
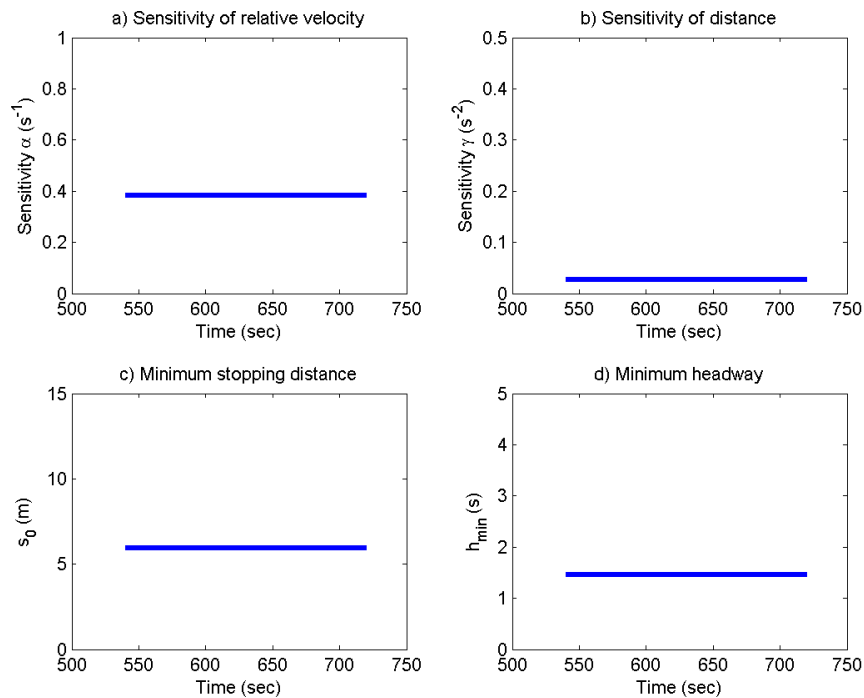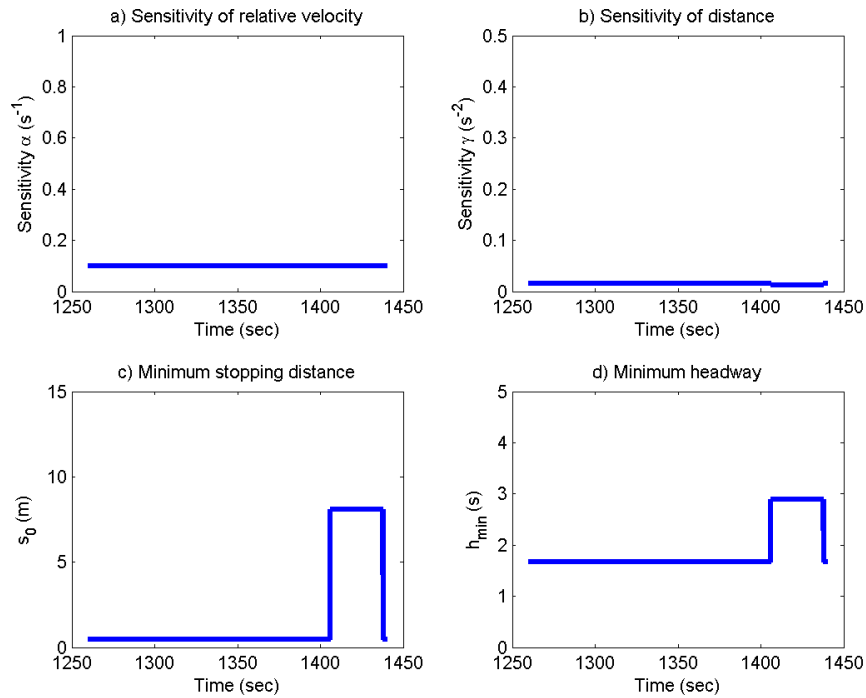
Figure 5.13: Parameters and estimated action points on 22$^{\text{nd}}$ October (normal driving).
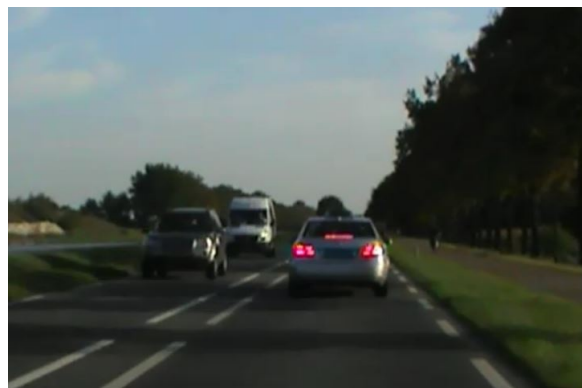
Figure 5.14: Image of the camera data on 22$^{\text{nd}}$ October at 570 sec (normal driving).

conditions cannot be captured because of limitations of the model.

The model that is used is a car-following model. The model is based on the relative velocity and relative distance between a car and the lead vehicle in order to estimate the acceleration of that car. Thus, when there is not a car-following task, the Helly model is not able to identify the behavior of the driver (acceleration) correctly. The same happens if there is a car in-front, but the relative distance with that car is very large. After the analysis of the results, it is found that a distance higher than 100 meters is considered from the model as a non-car-following task.
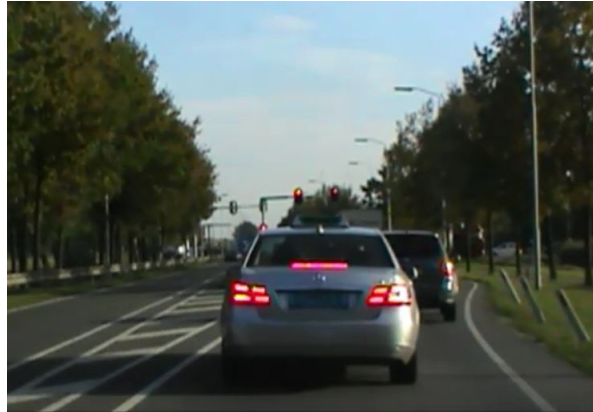
Figure 5.15: Image of the camera data on 22nd October at 660 sec (normal driving).

Figure 5.16: Image of the camera data on 23rd October at 1310 sec (normal driving).

The use of the Helly model and its car-following task is also related with the bad estimation that is observed when there is large steering or when the car changes lanes. The large steering may have different causes as change of lanes, sharp curves, turns in other roads, move to an on-ramp or off-ramp. The change of a lane lasts about 4 to 5 seconds and usually the driver decides to change a lane when he moves behind a slower car. In that case he decides to take action when the relative distance gets lower than 20 meters. For the 4 or 5 seconds that the car performs the action, there is no relative distance and velocity. After the change a new relative distance and relative velocity are recorded, but for the 4-5 seconds when the change is performed, the model is not able to make an estimation. The same happens with the sharp curves (or ring roads), where the lead vehicle instantaneous is not recognized due to the large angle (Figure 5.22). The change of a road and the movement of the car towards an on-ramp or an off-ramp face the same difficulty in the estimation due to the instantaneous loss of the car-following task. An exception to all those cases is the movement of the lead car simultaneously with the experimental car, which means change of a lane at the same time, or turn to another road simultaneously. For the movement in a sharp curve an exception is noticed when the cars are moving with a very small relative distance, so that the car following task is continuously recognized.

Figure 5.17: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points on 23rd October in the morning (normal driving).

The movement of the car on a secondary road is not analyzed in this project. However, there are some data sets where the car enters or leaves a secondary road and moves for a while on it. From observation of the results, it is noticed that the estimation is not possible due to the continuous change of the car-following task in the secondary roads. There, cars appear and disappear continuously from/to side roads and as results the car-following task changes all the time. However, in the limited cases where the same car stays in-front of the driver and there is no large steering, the estimation can be correct.

Figure 5.18: Parameters and estimated action points on 23$^{\text{rd}}$ October in the morning (normal driving).

Figure 5.19: Image of the camera data on 23$^{\text{rd}}$ October at 1480 sec (normal driving).

The last limitation of the proposed model is the deceleration of the ego car. As it is explained before, when the ego car starts accelerating suddenly, the estimation is partly possible since there is a large relative distance and the acceleration is anticipated by the model. The deceleration of the ego car, however, is the most problematic regardless the relative distance between the two cars. From the extreme driving experiments it was observed that the sudden deceleration cannot be captured by the model when the rela-
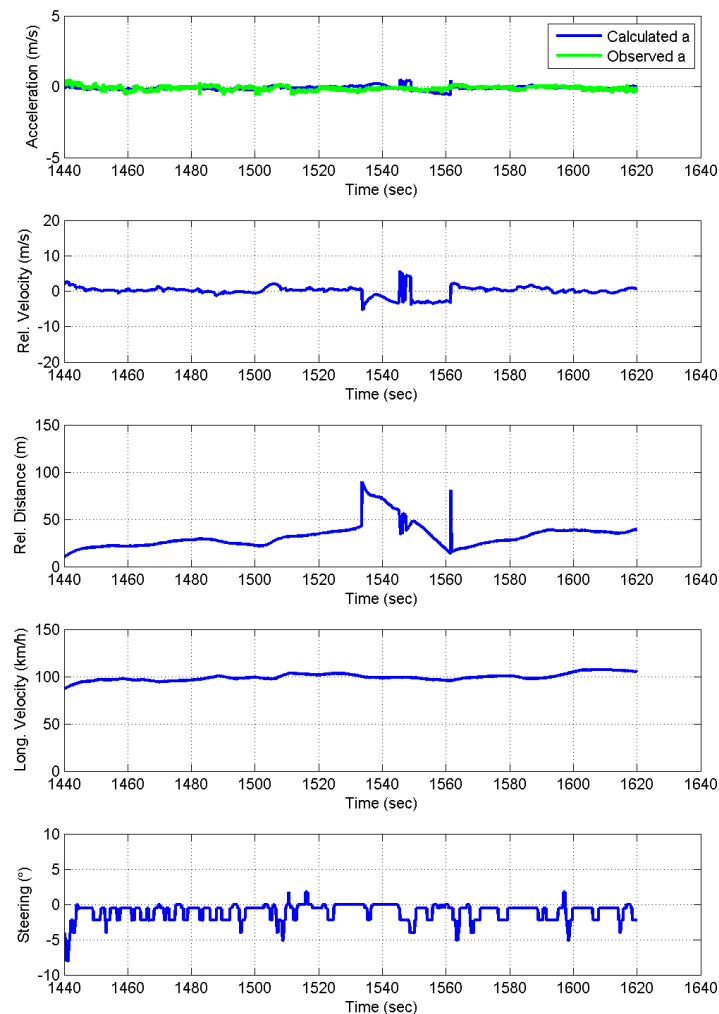
Figure 5.20: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points on 23rd October in the morning (normal driving).

tive distance is high since the sudden deceleration is not anticipated. The same happens when the relative distance is small and the relative velocity between the two cars is quite the same. An example in this case (found by the analysis) is a longitudinal velocity of 70 km/h and a relative distance lower than 20 m. In that case, if the lead car brakes suddenly, the driver of the car is surprised and reacts by pressing the brake pedal. This lasts very few seconds and the proposed model cannot recognize it. This phenomenon is also observed when the car needs to decelerate in a traffic light and the lead car brakes continuously due to traffic. In that case the driver of the ego car brakes as a reaction of the movement of the car in-front but this reaction is not captured by the model.
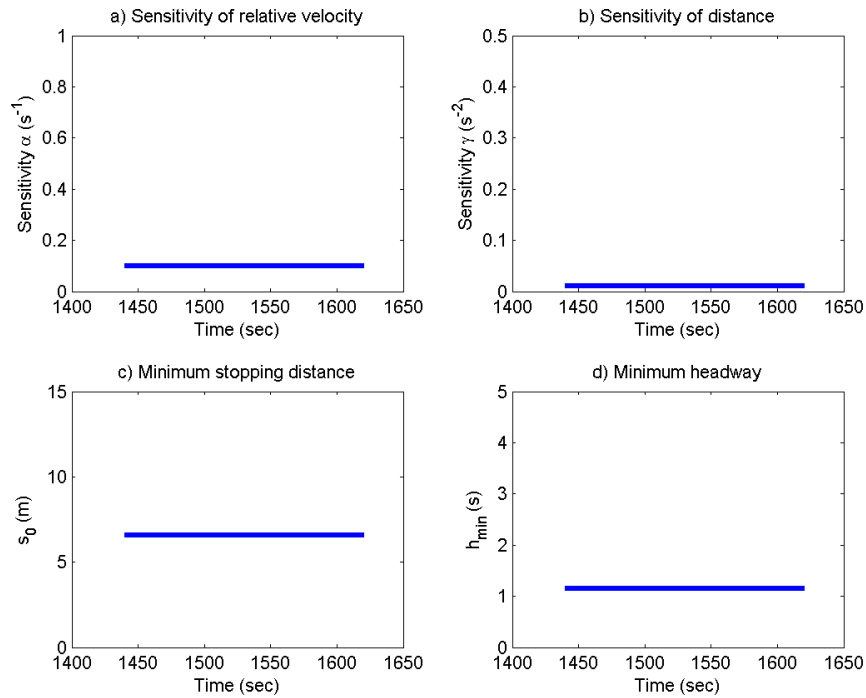
Figure 5.21: Parameters and estimated action points on 23rd October in the morning (normal driving).
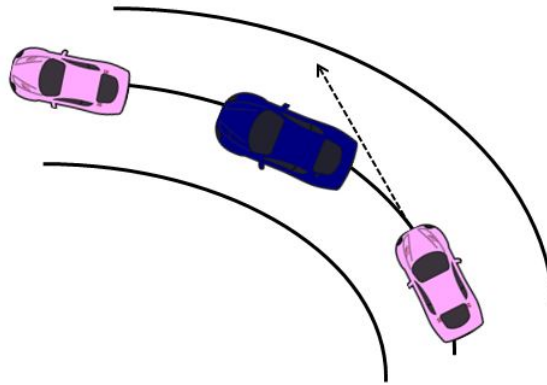
Figure 5.22: Limitation of the proposed system in sharp curves.

After the conditions under which the proposed model is not able to offer reliable results, a second list is made which summarizes the conditions under which the driver changes his driving style (Table 5.3). Usually the traffic light is a factor that influences the driver to change his driving style. Towards a traffic light the driving style does not change unless the car in-front brakes suddenly as it is described in previous paragraphs. After the traffic light usually the drivers adopt a different driving style. The on-ramps and off-ramps do not influence the driver but all the tests were made in uncongested conditions and that

Table 5.2: Limitations of the proposed system.

Condition	Reason for limitation
Not car in-front (n+1)	Helly model definition
Relative distance > 100 m	Helly model definition
Large steering (n)	Helly model definition (exception)
Change of lanes (n)	Helly model definition (exception)
Sharp curves	Helly model definition (exception)
Change of road	Helly model definition (exception)
Sudden deceleration (n)	Helly model limitation
Secondary road	Helly model definition (exception)

Table 5.3: Influence of driving conditions in the driving style.

Category	Driving style
Towards traffic light	No change
After traffic light	Change
On-ramp	No change
Off-ramp	No change
Composition of traffic	No change
Truck (position n+1)	No change
Moving block (position n+1)	Change (not confirmed)
Traffic state	Change
Change of car (position n+1)	No change (exception)
Change of lane	Change (exception)
Traffic barriers	-
Dynamic speed limits	-

is why the cars coming or going to ramps had no influence on the experimental car.

The composition of traffic has no effect on the behavior of the driver. That means that the driving style is the same no matter if in the next lane trucks or passenger cars are moving. The same happens if a truck is moving in-front of the driver. However, there was a case when the truck in-front was moving at very low speed (acting as moving block) and there was only one lane per direction. In this case, the driver was forced to change his driving style and move with the driving style of the truck. Since this happened only one time, it is not totally confirmed whether the moving block is a condition under which the driving style changes.

As with the moving block, the car adopts a different driving style when there is traffic in the road. That is logical since in the beginning the car moves with a free car-following task (large relative distance, high velocity) but when it finds traffic, it has to keep a small relative distance and move slower. The whole attitude of the driver is different and this is mostly noticed in the transition from one state to the other. What is not examined is the

Table 5.4: Usual values of the parameters in normal driving.

Parameters	Usual values for the same driver.
α	0.1 or 0.3 s^{-1}
γ	0.02 s^{-2}
s_0	-
h_{min}	between 0.9 - 2.0 s

behavior of the driver in different levels of traffic, but there were not any data available with such conditions.

A change in the driving style is noticed when the car changes lanes. Usually, there are totally different conditions in the next lane and the driver has to adapt to a different driving style. The only case that the driving style does not change is the existence of similar conditions in the new lane (almost same relative distance and velocity with the new lead car as with the old). However, this is very rare since the driver usually decides to change lane in order to put himself in a different condition (usually higher speed or no lead vehicle or better visibility).

When the car in-front leaves the lane and there is still another car there which offers almost the same relative distance and speed, the driver is not influenced by that change. The same happens when another car enters the lane but the space difference with the previously existing car is very small. In those cases, no change in the driving style is noticed since the driving conditions are almost similar.

Finally, there were two conditions observed in the road but their effect is not able to be analyzed due to other conditions that had a stronger influence on the driving style at that time. The first observation was the existence of dynamic speed limits in the road. Unfortunately, the driver was forced to move with a low speed due to small relative distance with his lead vehicle so the effect of the dynamic speed limit on the behavior of driver could not be recognized. The other condition was the change of the traffic barriers from concrete to metallic. At that time, there was no car-following task, thus the estimation was not successful and no further conclusions could be made.

From the observation, the analysis and the evaluation of all the results, the behavior of the driver because of factors related with the road infrastructure (on-ramps, off-ramps, secondary road, barriers), the traffic lights, the other cars in the network (composition of traffic, movement of the other cars) and the actions of the driver (change of lanes) is identified. An interesting conclusion is the use of specific values for the parameters for the same driver under similar conditions. It is found that in most of the cases that car-following conditions occur, the driver uses a specific set of parameters even in different days or times (Table 5.4). For the parameter α he uses the value 0.1 sec^{-1} when he is moving with an average speed of 70 km/h and the value 0.3 sec^{-1} when he is moving

Table 5.5: Summary of all the parameters in all the tests.

Tests	α	γ	s_0	h_{min}	Driver
ACC	0.23 s^{-1}	0.02 s^{-2}	1.00 m	1.60 s	a
Driver	0.23 s^{-1}	0.02 s^{-2}	8.00 m	2.10 s	a
Extreme driving	0.1 s^{-1}	0.01 - 0.03 s^{-2}	-	0.9 - 3.00 s	a
Normal driving	0.1 or 0.3 s^{-1}	0.02 s^{-2}	-	0.9 - 2.00 s	b

with a higher average speed of about 100 km/h. The parameter γ takes the value of 0.02 regardless the average speed (this value is the one proposed in the literature as well). The stopping distance does not have a specific value since its significance in the model is very small. The minimum headway usually takes values between 0.9 to 2.0 seconds, but again its significance is small. The higher the moving speed of the vehicle the closer the value of the minimum headway is to 0.9 seconds.

The above finding about the parameters and their constant values demonstrates that the proposed system can cover the heterogeneity between the same driver. That means that a future application could recognize specific set of parameters for the driver when performing a simple car-following task. By doing this, a driving style can be attributed to the driver without estimation, since the parameters of the model would be known.

In Table 5.5 a complete list is created of the values of the parameters that were observed from all the tests. The minimum stopping distance does not have an average value in all the tests. The minimum headway does not take values higher than 3 seconds even when different drivers are behind the wheel and even when different conditions exist in the road. In extreme driving the values of the minimum headway can get higher (around 3 seconds) and the reason for that can be the sudden decelerations and accelerations (large values). For those values, a large headway is desired for the movement to be safe. The same reasoning could be applied to the stopping distance but its limited significance in the model does not permit the derivation of any conclusion. The sensitivity of distance differences γ takes the value 0.02 seconds which is proposed in the literature, even if different drivers or different conditions occur in the road. This parameter takes higher values when the driver decelerates suddenly. In the sudden decelerations the existing relative distance between the ego car and its lead vehicle is not the desired by the driver and for that reason he decelerates suddenly. The higher values of the parameter in these sudden decelerations are logical since the distance differences play a significant role in the decision of the driver for deceleration. The sensitivity of relative velocity takes values between 0.1 to 0.3 s^{-1}. These values are influenced from the longitudinal velocity of the ego vehicle. When the vehicle moves with lower speeds, the driver values less the relative velocity of the lead vehicle (how fast the lead vehicle goes) in his decision to accelerate or decelerate. From the other hand, when the vehicle moves with high speed, it is important to take into consideration the relative velocity with the lead vehicle before a decision is taken for accelerating and decelerating. This justifies the higher values of the sensitivity parameter.

The above mapping of the parameters and their explanation from a behavioral point of view offers a better view of the results and explains the changes of the parameters based on the conditions on the road. As it is stated before, the analysis of the parameters covers the intra driver heterogeneity. The behavioral analysis of the parameters is made from a general view and results from both drivers are included and are explained in the same way. From the changes of the parameters between the sets of the two drivers it can be seen that the parameters have the same rate of change. A recommendation would be a unified model that would propose unified sets of parameters under specific conditions for groups of drivers with similar characteristics.

5.3   Performance of the model

In the two previous sections, the results of the estimation model are presented and are analyzed. In this section an evaluation of the proposed system is made. For the current evaluation the data from the 22nd October are used since they are the largest in quantity and a better overview can be made. First, the performance of the genetic algorithm is presented regarding the accuracy level that is set in the system. Four different levels of accuracy are tested: 0.1 m/s^2 (higher accuracy), 0.3 m/s^2, 0.6 m/s^2 and 0.9 m/s^2 (lower accuracy). A performance level is calculated for each valid step of the analyzed data. The performance of each step is the number of data points with accuracy in the desired levels divided with the total number of data points (Equation 5.1):

$$P = \frac{n_s}{n} \qquad (5.1)$$

$$n_s = \sum_{i=1}^{n} i, A_i < A \qquad (5.2)$$

The performance of each step is described by P, n is the total number of data points in that step, n_s is the number of data points where the accuracy is higher than the initial set value, A_i is the calculated accuracy from Equation 4.5 (difference of calculated and observed acceleration) and A is the initial accuracy set in the system e.g. 0.1 m/s^2.

In Figure 5.23, the performance of the genetic algorithm in the four different levels of accuracy is tested (1000 generations and 30 repetitions). The number of the data sets in the x axis is the same which was used in the first column of Table 3.6. The reason for that is that it is easier to relate the number of each part with the time that it happened and from the Appendix B observe the whole analysis. As it can be seen, the genetic algorithm has a better performance if the accuracy level is lower. The reason for that is
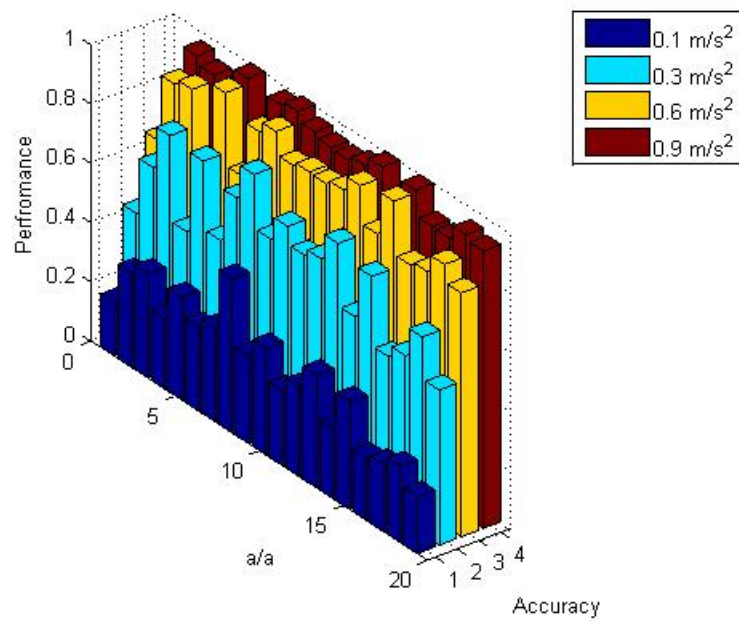
Figure 5.23: Performance of the genetic algorithm in different levels of requested accuracy.
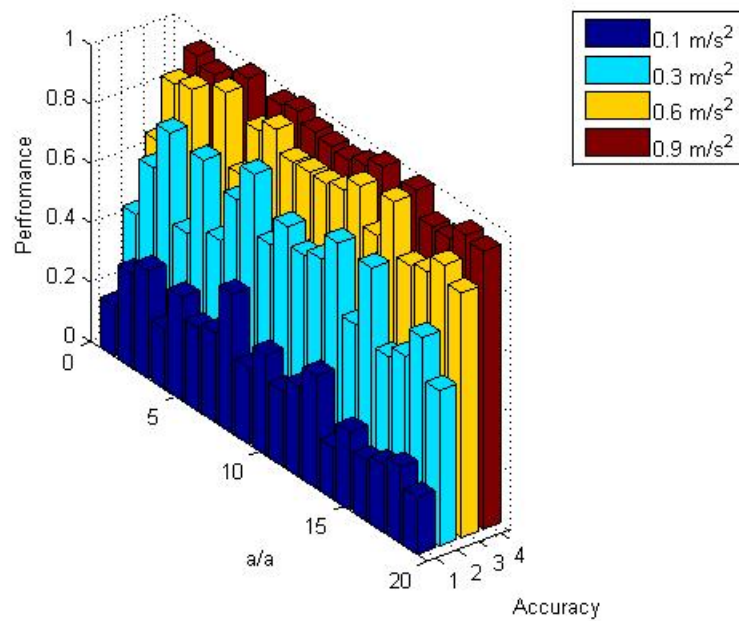
Figure 5.24: Performance of the unconstrained nonlinear optimization method in different levels of requested accuracy.

the acceptance of higher differences between the observed and the calculated accelerations.
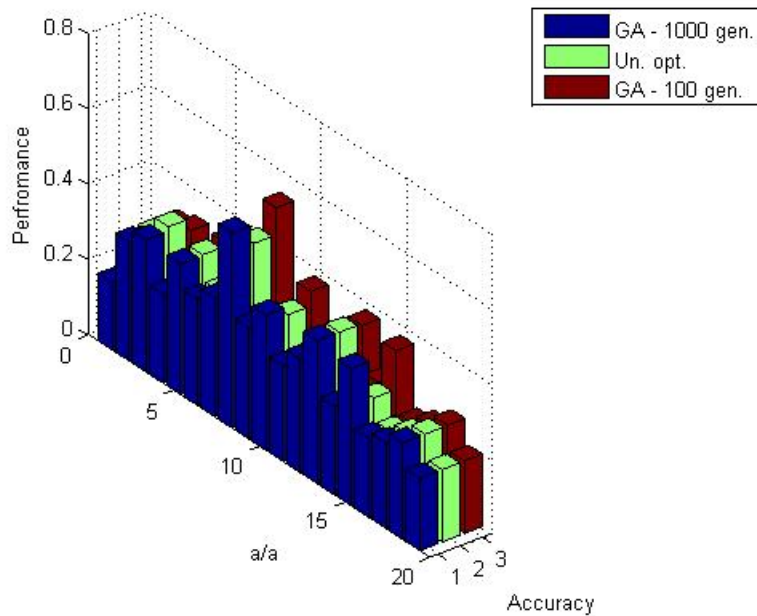
Figure 5.25: Performance of the unconstrained nonlinear optimization method in different levels of requested accuracy.

Table 5.6: Number of action points identified with each accuracy level.

Accuracy level	Action points
0.1 m/s^2	18
0.3 m/s^2	6
0.6 m/s^2	4
0.9 m/s^2	0

In addition to the genetic algorithm, the system is tested with an unconstrained nonlinear optimization method. The main appeal in using that method is the reliability of the results, in other words the optimization, in contrast with the genetic algorithm, reaches the exact same results no matter how many times the procedure is repeated. Another reason for the choice of that method is the time needed to make the estimation. As it can be seen in Figure 5.24 the performance is better when the accuracy level is lower, as it happens in the genetic algorithm.

From the other hand, the number of action points which are identified is proportional to the level of accuracy. The higher the accuracy level, the more the action points which are estimated. The number of action points which are identified with each accuracy level is shown in Table 5.6.

In the end, the performance of the model between the two methods is tested. In Figure 5.25, the performance of the genetic algorithm with 1000 generations (30 repetitions) is

Table 5.7: Real-time application options.

Method-Option	Accuracy	Performance	Time for Estimation
GA (1000 generations, 30 repetitions)	0.1 m/s^2	29.6%	4.5 hours
GA (1000 generations, 30 repetitions)	0.3 m/s^2	65.8%	4.5 hours
GA (1000 generations, 30 repetitions)	0.6 m/s^2	85.9%	4.25 hours
GA (1000 generations, 30 repetitions)	0.9 m/s^2	91.8%	4.15 hours
GA (100 generations, 30 repetitions)	0.1 m/s^2	29.3%	0.5 hours
Initial parameters (every step) (GA, 1000, 30)	0.1 m/s^2	29.6%	4.5 hours
Unconstrained nonlinear opt	0.1 m/s^2	27.9%	3 minutes
Unconstrained nonlinear opt	0.3 m/s^2	65.7%	3 minutes
Unconstrained nonlinear opt	0.6 m/s^2	86.0%	3 minutes
Unconstrained nonlinear opt	0.9 m/s^2	91.9%	3 minutes
Initial parameters (Un. optimization)	0.1 m/s^2	28.0%	3 minutes

compered with the performance of the genetic algorithm with 100 generations (30 repetitions) and the performance of the unconstrained nonlinear optimization. The requested accuracy is 0.1 m/s^2. As it can be observed, the genetic algorithm reaches the same performance even with less generations. The unconstrained nonlinear optimization offers almost the same results with the genetic algorithm, the genetic algorithm surpasses a little bit the unconstrained nonlinear optimization in a few cases. Hence, the identification is independent of the optimization method that is used.

5.4 Real-time application options

In the previous section the performance of the proposed system is evaluated. In this section, the performance is compared with the time needed to make the estimation. The objective of this comparison is the selection of the better choices and conditions that can be used in a real-time application for the identification of the driving behavior. All the calculations were performed using Matlab R2012_b on a Pentium Dual Core @2.1 GHz computer system with 3.00 GB RAM running on Windows 7 64-bit.

As it was stated in the previous section, the higher the accuracy level of the genetic algorithm or the unconstrained optimization, the lower the performance of the proposed system. This is also obvious from Table 5.7 where the average performances of all the steps are calculated. The ratio between the average performances is higher in the higher accuracy levels (65.8/29.6 = 2.22) and lower as the accuracy levels get lower (91.8/85.9 = 1.07). The time needed for the genetic algorithm for the estimation is getting lower as the accuracy level decreases but the difference is negligible. However, the difference in time is significant when fewer generations are selected while the performances stay in the same levels.

The time needed for the estimation with the unconstrained nonlinear optimization is 3

minutes regardless the accuracy level. This time is significant lower than the time needed with the genetic algorithm while the performances stay in almost the same levels. That is why it is recommended to use the unconstrained nonlinear optimization for a real-time application since it gives reliable results much faster. The accuracy level that is recommended to be used is 0.3 m/s^2 since the performance is rather high (much higher than with 0.1 m/s^2 accuracy) and one third of the action points are estimated (6 instead of 0 with 0.9 m/s^2 accuracy).

The last test that is made is the use of the initial parameters proposed in the literature in every new step. The results are the same with the use of the new estimated parameters in each step which shows that the optimization method reaches the optimum result regardless the values of the initial parameters and the time needed to reach optimum results is the same in both cases.

5.5 Brief summary and discussion of the results

In this chapter, the outcome of the parameter estimation model is presented and analyzed. First, some results of the three tests are shown in graphs where the observed and calculated signals are included as well as the calculated parameters. Then, an evaluation of the results is made in which the limitations of the model are presented and are explained, the action points are correlated with the conditions of the driving environment and a behavioral explanation of the calculated parameters is given. Finally, the performance of the model is presented and the optimization tools used in the proposed system are compared in order to determine the best option for a real-time application.

In the test with the ACC and the driver the parameter estimation procedure is successful. The expected action points from the data analysis in Chapter 3 are verified and observed in the results of the parameter estimation system. Also, indications about the use of specific set of parameters for each driver under simple car-following conditions are observed. In the test with the extreme driving, the estimation procedure is not successful in sudden decelerations of the ego vehicle. However, the necessary observations to calibrate the system are made (criteria for not making a second optimization in the proposed system, Chapter 4). More indications about the limitations of the proposed system are observed with the most important being the use of a car-following model for the estimation which cannot be accurate when there is not a car-following task. The last test with normal driving verified the observations for limitations of the car-following model since the parameter estimation is only successful when car-following conditions occur. Furthermore, the received data in case there is large steering are incorrect (most of the times) and this complicates the estimation procedure. The wrong incoming data are due to failure of the data collection system which recognizes static and dynamic objects (e.g. traffic lights, vehicles in the next lane) as lead vehicles.

In the evaluation of the results it becomes clear that the use of the Helly model (and in general the use of a car-following model) limits the proposed system. The car-following model is selected because a similar research for identification of action points had not been performed in the past and it seemed more appropriate to start the research from simple conditions (as the car-following task). However, the system is tested in normal driving where there is not always a car-following condition and as a result the estimation cannot be successfully performed. It is recommended to use a 3-regime model in the future that gives different equations for the car-following conditions, for the free-flow moving and the acceleration and deceleration. Such a model is expected to capture the limitations of the car-following model, not only the criterion for the existence of a lead vehicle but also the sudden movement of the ego car (sudden decelerations).

The conditions that are identified as action points are logical and they were expected from the state-of-the-art review. The infrastructure characteristics like on-ramps are not recognized as action points but the traffic conditions in all the experiments were not appropriate (very low traffic) for a proper statement to be derived. Since the parameter estimation approach is successful, more tests are necessary from future researches in order to verify the action points and their relationship with the driving environment. It has to be noted again that the use of a different model is a necessary condition before more tests are made.

The mapping of all parameters and the tests give an insight of the reasons why the changes in the parameters occur. These reasons are based on a mathematical analysis of the Helly model and the interaction between the different variables in the used equations. The change of the parameters are explained from a mathematical perspective and the explanations are logical. Also the changes in the parameters are analyzed from the behavioral point of view and the outcome of the analysis is also logical.

Finally the performance of the model showed that the genetic algorithm is not a good option for a real-time application especially when there are available other tools like the unconstrained nonlinear optimization that can offer the same results in few minutes. The initial suggestion that the genetic algorithm would offer better results is not valid since the comparison between the two optimization tools shows a slight difference in favor of the genetic algorithm which is almost negligible if the execution time is considered. The only argument in favor of the genetic algorithm that can be made is the use of limited stopping criteria, while, if a fitness limit criterion was used, the computation time could have been less.

Chapter 6

Conclusions and recommendations

The behavior of the driver is very important in the formulation of traffic flow models. In this project, the main objective is the construction of a system that can identify the behavior of the driver by using vehicle-based signals. The vehicle-based signals that are used are the longitudinal velocity and acceleration, the steering, the relative speed and the relative distance. Three different experiments are conducted in order to obtain all the necessary data. The first two experiments are performed with extreme driving conditions and with the use of the Adaptive Cruise Control in order to collect the necessary data to calibrate the model. Then, a testing is conducted with normal driving conditions to validate the proposed model.

After the data analysis, the input data are used to estimate the parameters in the Helly car-following model. The Helly model uses the relative velocity, the relative distance and the longitudinal acceleration of the car and produces the longitudinal acceleration. The parameters in the Helly model that need to be estimated are the sensitivity of relative speed, the sensitivity of distance differences (between the relative distance and the desired distance), the minimum stopping distance and the minimum headway.

The proposed methodology uses an optimization procedure to determine the optimum parameters of the Helly model so that the calculated acceleration matches the observed acceleration. The root mean square error is used as an objective function and the boundaries in the parameter values are set from the literature. The estimation is made through a moving window of three minutes and a constant set of parameters is assumed for the whole window. In the parts where the accelerations differ significantly after the estimation is performed, a second estimation takes place. By doing this, different set of parameters are observed for the parts where the driver changes his driving style.

The final step is the identification of the actions points where the parameters change due to factors of the driving environment. The system identifies the points where the set of parameters changes and a second estimation is needed as action points. The correlation of the driving factors and the actions points is made from the observation of the estimation results and the camera data.

6.1   Answers to the research questions

The main objective of the graduation project is to identify the behavior of the driver, determine where this behavior changes and correlate the changes in the driving behavior with changes in the driving environment. In the beginning of this report, six research questions are formatted which lead the research to complete the main objective. Some small indications on the answers of the research questions are presented in Chapter 1. Here, the explicit answers to the research questions are presented.

1. What are the components of the driving environment that influence the behavior of the driver and which of them are more important in a car-following scenario?

The factors that influence the driving behavior can be separated in three different categories: the factors of the outside driving environment, the factors from the inside the vehicle environment and the driver himself. The factors from the inside the vehicle environment are the navigator system, the mobile phone, other passengers, etc. These factors are not analyzed in this thesis since the objective of the thesis is to identify the behavior of the driver in a baseline scenario when no other information (from in-vehicle systems or factors) is coming to him. The factors concerning the driver himself are not included in the thesis since the available data do not have a large variation in driver characteristics. The components of the outside driving environment which influence the driver's behavior in highways are the traffic lights and the traffic signs, the possible static or dynamic obstacles (trees, people, animals, rocks), the road and infrastructure characteristics, the weather conditions and the traffic flow in the network. In this sense, from literature it follows that the existing traffic flow in the network (congestion) is the most important parameter. Driving behavior is strongly influenced from the traffic state, the traffic composition and the movements of the other cars in the road. Also, the influence of the road infrastructure and the traffic lights and signs are analyzed in this project, since they have been observed from the available data. The dynamic and static obstacles can have a large influence in the driving behavior but they are not included in this thesis since they are rarely observed in highways and in case they are directed to appear in the road the recorded data are not accurate anymore as the "surprise" characteristic of the obstacles is lost.

2. What data can be used in order to identify the driver's behavior?

Different types of data can be used for the identification of the driving behavior such as behavioral measurements, vehicle-based signals, interviews, GPS data, etc. Most existing studies use behavioral data to identify the driving behavior from the driver's perspective. In other words, they explain how complex can the driving task be for the driver. From the studies that use vehicle based signals, the steering measurement is usually used to identify the actions of the driver (e.g changing lane). In this project, two types of data are used in order to identify the driver's behavior, the vehicle-based signals and the camera data, since they offer more accurate identification results, they are not extensively used in

the literature and they can explain the driving behavior for the combined driver-vehicle system. In other words, they show the vehicle's behavior as a result of the actions of the driver and the vehicle dynamics. The vehicle-based signals that have been used are the velocity of the vehicle, the longitudinal acceleration, the steering and the relative speed and distance to the lead vehicle. The camera data are used in order to relate the behavior of the driver to the driving environment.

3. Which car-following models can be used in order to estimate the driver's behavior?

There are a lot of different models that could be used in the determination of the driver's behavior. Three main categories are analyzed: the stimulus-response models, the safety distance models and the psycho-spacing models. The stimulus response models are selected for this thesis since they are able to show the dynamic interactions between other vehicles in the same lane, they are simple to analyze and understand, and even analytical results can be derived from them. From the stimulus-response models, the IDM and the Helly model are selected since they consider the effect of the relative spacing independently from the relative velocity and they have been proved appropriate in capturing the behavior of the driver from large data sets. Although both models are tested, the Helly model gave better better fitting results than the IDM and the values of the parameters of the Helly model could be explained unlike the values of the parameters of the IDM that not always made sense. Thus, in the end the Helly model is used for the driving behavior identification.

4. How can the parameters of the car-following models be estimated?

The parameters of the car-following models is estimated through a derivation of a statistical parameter estimation approach. An optimization method to estimate the parameters of the car-following model is used which minimizes the difference between the calculated and the observed acceleration. The continuous changes in the driving environment require a time-variant estimation approach and for that reason the optimization is performed with a moving estimation window of 3 minutes. The choice of the estimation window is made based on the need for a visual representation of the results (in order to identify the action points) and the observation that the driving style changes in less than 3 minutes in normal driving and a constant set of parameters cannot be applied in a larger time window. The parameter estimation procedure with a constant set of parameters is made based on the observation that a constant set of parameters can produce a very good identification of the driving behavior as long as the driving style stays the same. Two different optimization methods are tested in order to compare the results and the computation times and propose the best alternative: the genetic algorithm and the unconstrained nonlinear optimization. The genetic algorithm is selected as the tool that can offer a solution very close to reality and the other tool as a fast method. The proposed system makes an optimization every three minutes and produces a constant set of parameter. Then, it checks if the difference between the accelerations is not the desired and performs a second

optimization for the parts where the accelerations differ.

5. How can the actions points (the threshold in which the parameters of the models change) be estimated?

The actions points are estimated from the outcome of the parameter estimation approach. The approach described in the previous research question determines a constant set of parameters for the whole moving time window. In the points where the accuracy (difference of accelerations) is not the desired a second optimization is performed. The beginning of the points where a second optimization is needed are identified as action points. Also, there are some parts where the accelerations differ more than the desired accuracy but a second optimization is not possible due to the limited time length of the difference between the observed and the calculated signal. These points are also considered as action points and their relationship with the driving environment is investigated.

6. To what extend can the action points be related to changes in the driving environment?

The actions points are related to changes in the driving environment through close observation of the camera data and visualization of the outcome of the parameter estimation method. Hence, from these observations, the conditions that are responsible for a change in the driving style are reported. These conditions are found to be the traffic lights, the moving blocks as lead vehicles, the change in the traffic state and the change of lanes. Furthermore, some driving factors that were initially expected to influence the driving behavior but they are not found to have any relationship with a change in the driving style are also noted. These factors are the on-ramps and the off-ramps, the composition of traffic and the change of the lead car. Finally, through the analysis of the results of the parameter estimation system, the limitations of the proposed model are demonstrated. These limitations make more difficult the identification of action points and their correlation with the driving environment.

6.2 Conclusions

In this thesis, a framework is proposed for the identification of the driving behavior through vehicle-based signals and the determination of the action points. The analysis of the results showed that the proposed system is reliable in general and can be used for the identification of the driver's behavior. The system is able to match the calculated acceleration with the observed acceleration from the vehicle-based signals. The Helly model from its definition as a car-following model has some limitations and the proposed model is able to perform well only under car-following situations. However, in the normal driving this is not always the case and as a result, there are some points where the matching of the accelerations is not successful. The main conditions under which the estimation is

not successful are the large relative distance, the large steering and the sudden braking of the lead vehicle.

After the analysis of the video, some driving factors are related to changes in the driving style. Those factors are the entering of the car into traffic congestion, the change of lanes and the traffic lights. From the other side, the driving style does not change when the car decelerates to a traffic light and when there is an on-ramp or an off-ramp in the road. Also, the driving style is not affected by the composition of the traffic and from the change of the lead car.

The parameters are found to be the same for the same driver under the simple car-following task. This finding is very important for future research since the parameters of the car-following model for each driver can be attached directly to the system and the estimation could be skipped in that case.

From the proposed system a number of action points is identified depending on the desired accuracy. The higher the accuracy the more points are identified. However, the proposed system is not able to identify the 100% of the action points that exist in the data. From the video analysis, all the data points are identified and in all the cases there are small mismatches between the accelerations. When these mismatches last very few seconds, the action points cannot be identified. Also, in the cases where the Helly model fails to make the estimation, the action points cannot be identified.

In the end a performance indicator is created based on the number of estimated data with the desired accuracy. The performance of the model is higher when the desired level of accuracy is lower. That is because higher differences between the accelerations are acceptable. Two different optimization tools are tested, the genetic algorithm and the unconstrained nonlinear optimization. The performance of the system is the same regardless the use of the optimization method, but the unconstrained nonlinear optimization is much faster.

6.3   Recommendations

The proposed model offers great opportunities in traffic management as well as in traffic safety. With this system, the behavior of the driver is known and it is easier to interfere and control the expected actions of the driver. In a real-time application the unconstrained nonlinear optimization can be used to identify the behavior of the driver every 4 or 5 seconds. In order to save time, some specific driving conditions can be related to specific sets of parameters that can be observed for each driver and can be attached directly without estimation to the driver. A further possibility can be the use of a unified set of parameters under specific conditions that can be used to a number of different drivers. For that reason, future research should include experiments with different drivers (a variety

of different age, gender, driving experience). Another possibility can be the estimation of the better set of the parameters from the model directly for each driver. This can be done after driving for some time and continuous identifications until the set of parameters for each driving conditions is found. However, for this recommendation enough hours of driving are needed as well as a variety of different conditions should appear in the road.

Except of general recommendations on the use of the system in the future, some recommendations on the proposed model and the research procedure are made. In future experiments, camera data should be always collected. Not only the collection is necessary but the matching of the collected data with the vehicle-based signals. For that reason a passenger is necessary that will keep record of all the actions of the driver and the car and the matching of the two data sources will be easier. Furthermore, some of the incoming data were found to be wrong when large steering was made. That is why the radar signals are recommended for future research since they are also available and they offer greater accuracy in the data.

In this thesis, only a limited number of driving conditions are tested which were found on the normal driving. In the future more factors should be analyzed. This can be made by setting up some road situations (e.g. accidents) or by selecting specific roads for driving where these conditions may appear (e.g. highly congested roads). Furthermore, the vehicle-based signals can be combined with behavioral data so that the behavior of the driver inside the car can be analyzed. By doing so, the reaction of the driver would be correlated with the driving behavior from the vehicle based signals and the general system of driver-vehicle-environment would be analyzed. In the analysis of the behavior of the driver inside the vehicle, the in-board camera data that are available can be very helpful.

The last proposal is related with the use of the Helly model. The Helly model as well as any other car-following model has a strong limitation which comes by its definition. To avoid the bad estimation in the situations where no car-following task takes place another model should be used. A good idea could be the use of the three-regime model described in Wagner [74] where a different model is considered in car-following situations, in acceleration and in deceleration.

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Appendices

Appendix A

Flow charts and Matlab code

The main Matlab script is given below:

```matlab
%  Copyright M. Panagopoulou

%  1. LOAD DATA

%  2. ESTIMATION PROCEDURE

step = 18000;   % 180 seconds
b_final = zeros(step, 4);
b0 = [0.20  0.02  8.00  1.00];   %  initial values, sensitivity for speed,
%  sensitivity of the distance difference, minimum stopping distance
%  and minimum headway

%  minimum and maximum values from literature
bmin = [0.10  0.01   0     0];
bmax = [1.00  0.50  15.00 5.00];

generations = 1000;     % number of generations
ga_optimize_times = 30;      % number of repetitions of the GA

Minimum_part = 2000;    %  for problematic parts
Error_part = 400;    %  for problematic parts
Accuracy = 0.1;
Performance = zeros((round(length(time)/step)),1);

%  create function call for GA
RunEstimation = @(vel, relvel, reldist, acc)...
RunGAMultiple(ga_optimize_times,...
generations, b0, bmin, bmax,...
vel, relvel, reldist, acc);

% create function call for unconstrained optimization
% RunEstimation = @(vel, relvel, reldist, acc) RunFM(b0, bmin, bmax, vel,...
% relvel, reldist, acc);
```

```matlab
j = 1;    % sequencial index

for i=step:step:length(time)
    stepStartIndex = (i-step+1);

    %  2.1: FIRST ESTIMATION WITH CONSTANT B
    reldist_step = reldist(stepStartIndex:i, 1);
    acc_step = acc(stepStartIndex:i, 1);
    steer_step = steer(stepStartIndex:i, 1);
    relvel_step = relvel(stepStartIndex:i, 1);
    vel_step = vel(stepStartIndex:i, 1);
    time_step = time(stepStartIndex:i, 1);

    b0 = RunEstimation(vel_step, relvel_step, reldist_step, acc_step);

    b_step = repmat(b0, step, 1);

    b_final(stepStartIndex:i,:) = b_step;

    %  2.2: FIND THE PARTS THAT THE ACCELERATIONS DIFFER
    a_temp = Helly(b_step, vel_step, relvel_step, reldist_step);

    diff = (abs(a_temp-acc_step));
    out = SelectedEstim(diff,Accuracy,Minimum_part,Error_part);

    partsNum = 0;
    if numel(out) > 0
        partsNum = length(out(:, 1));
    end

    for k=1:partsNum

        partStartIndex = stepStartIndex + out(k,1);
        partEndIndex = stepStartIndex + out(k,2);

        reldist_part = reldist(partStartIndex:partEndIndex, 1);
        acc_part = acc(partStartIndex:partEndIndex, 1);
        relvel_part = relvel(partStartIndex:partEndIndex, 1);
        vel_part = vel(partStartIndex:partEndIndex, 1);
        steer_part = steer(partStartIndex:partEndIndex, 1);

    %  2.3: CHECK CONDITIONS

    %  criteria 2.3.1: check reldist>100
    if any(gt(reldist_part, 100))
        disp ('No identification in this period');
        b_final(partStartIndex:partEndIndex,:) = zeros(((out(k,2)-...
        out(k,1))+1), 4);
        continue;
    end
```

```matlab
    %  criteria 2.3.2: check steering and acceleration differences
    smax = (max(steer_part))*(180/pi);
    smin = (min(steer_part))*(180/pi);
    amax = max(acc_part);
    amin = min(acc_part);
    sdiff = abs(smax - smin);
    adiff = abs(amax - amin);

    if sdiff > 5 && adiff > 5
        disp ('No identification in this period');
        b_final(partStartIndex:partEndIndex,:) = zeros(((out(k,2)-...
        out(k,1))+1), 4);
        continue;
    end

        b_part = RunEstimation(vel_part, relvel_part, reldist_part,...
         acc_part);
        b_final(partStartIndex:partEndIndex,:) = repmat(b_part,((out(k,2)...
        -out(k,1))+1),1);

    end

    %  2.4: PLOTTING

    %  2.5: PERFORMANCE

    a_final = Helly(b_final(stepStartIndex:i,:), vel_step, relvel_step,...
     reldist_step);

    diff_final = abs(a_final - acc_step);
    performance_temp = lt(diff_final,Accuracy);
    Performance(j,1) = sum(performance_temp)/step;

    j = j +1;

end

%  3. SAVE RESULTS
```

The main Matlab script calls some functions which are also presented in the next pages.

The "RunGA" function which includes the genetic algorithm:

```matlab
% Copyright M. Panagopoulou

function [b, fval] = RunGA(generations, bInitial, bmin, bmax, vel,...
    relvel, reldist, acc)
```

```matlab
options = gaoptimset('InitialPopulation',bInitial,'FitnessLimit',0,...
    'CrossoverFcn',@crossoverarithmetic,'Generations',generations,...
    'StallGenLimit',100000,'display','iter');

nvars = 4;     % Number of variables

%  anonymous function that calls the objective with arguments
fhandle = @(b) Objective(b, vel, relvel, reldist, acc);

[b,fval,exitflag,output,population,scores] = ga(fhandle,nvars,[],...
            [],[],[],bmin,bmax,[],options);

end
```

The "RunGAMultiple" function in order to run the genetic algorithm several times to avoid local optimums:

```matlab
%  Copyright M. Panagopoulou

function  [b_opt] = RunGAMultiple(times, generations, bInitial,...
    bmin, bmax, vel, relvel, reldist, acc)

    fval_opt = 0;

    for m = 1:times

        [b,fval] = RunGA(generations, bInitial, bmin, bmax, vel, relvel,...
            reldist, acc );

        if m == 1
            b_opt = b;
            fval_opt = fval;
            continue
        end

        if fval < fval_opt
          fval_opt = fval;
          b_opt = b;
        end

    end

end
```

The "Objective" function which includes the fitness function for the optimization:

```matlab
function F = Objective(b, vel, relvel, reldist, acc)

    rddes = b(3) + b(4) .* vel;
    %  Desired distance

    ds = reldist - rddes;
    % Difference desired distance & current distance

    a = b(1) .* relvel + b(2) .* ds;

    n = length(a);

    F = sqrt((sum((a-acc).^2))/n);     %  RMSE
end
```

The "Helly" function which includes the Helly model:

```matlab
function a = Helly(b, vel, relvel, reldist)

    rddes = b(:,3) + b(:,4) .* vel(:,1);
    %  Desired distance

    ds = reldist(:,1) - rddes;
    % Difference desired distance & current distance

    a(:,1) = b(:,1) .* relvel(:,1) + b(:,2) .* ds;

end
```

The "SelectedEstim" function which selects the problematic parts that need a second optimization:

```matlab
%  Copyright M. Panagopoulou

function [out] = SelectedEstim(input, threshold, inSeq, gapMargin)

    %  find elements greater than threshold
    temp = gt(input, threshold);

    %  find all zeros
```

```matlab
temp = find(temp == 0);

if isempty(temp) && length(input) >= inSeq
    % the whole input is greater than threshold and in sequence
    out(1, :) = [1 length(input)];
    return;
elseif isempty(temp) || length(temp) == length(input)
    % the whole input is greater than threshold
    % OR
    % the whole input is less than threshold
    return;
end

startIndex = 0;
endIndex = 0;
out = [];
j = 0;      % start with 0 as it is pre-incemental

% find where gaps of 1-s exist that are greater than the margin
for i=1:length(temp)

    indexValue = 0;

    % if first occurence is the end of a sequence greater than inSeq
    if i == 1 && temp(i) >= inSeq
        j = j + 1;
        out(j,:) = [1 (temp(i) - 1)];
    end

    if i + 1 > length(temp)
        % if end of array check if in sequence until end of original
        % array (input)
        indexValue = length(input);
    else
        indexValue = temp(i + 1);
    end

    % if gap less than asked in sequence, continue on
    if (indexValue - temp(i)) < inSeq
        continue;
    end

    % find start and end of the sequencial 1-s
    tempStartIndex = temp(i) + 1;
    tempEndIndex = indexValue - 1;

    % is the gap with the previous sequence bigger that the margin?
    if endIndex > 0 && tempStartIndex - endIndex <= gapMargin

        % consider it as part of the previous sequence
        endIndex = tempEndIndex;
    else
```

```matlab
            %  consider it as a new sequence
            startIndex = tempStartIndex;
            endIndex = tempEndIndex;
            j = j + 1;
        end

        %  add the subarray to the output as a cell
        out(j,:) = [startIndex endIndex];

    end

end
```

The "RunFM" function which executes the fminsearch (unconstrained nonlinear optimization) with up and low boundaries:

```matlab
function [b, fval] = RunFM(bInitial, bMin, bMax, vel, relvel, reldist, acc)

% anonymous function that calls the objective with arguments
fhandle = @(b) Objective(b, vel, relvel, reldist, acc);

[b,fval] = fminsearchbnd(fhandle,bInitial, bMin, bMax);

end
```

The analytic flow chart of the above code is given in Figure A.1. The flow chart for the selection of the problematic parts (function "SelectedEstim") is presented in Figure A.2.
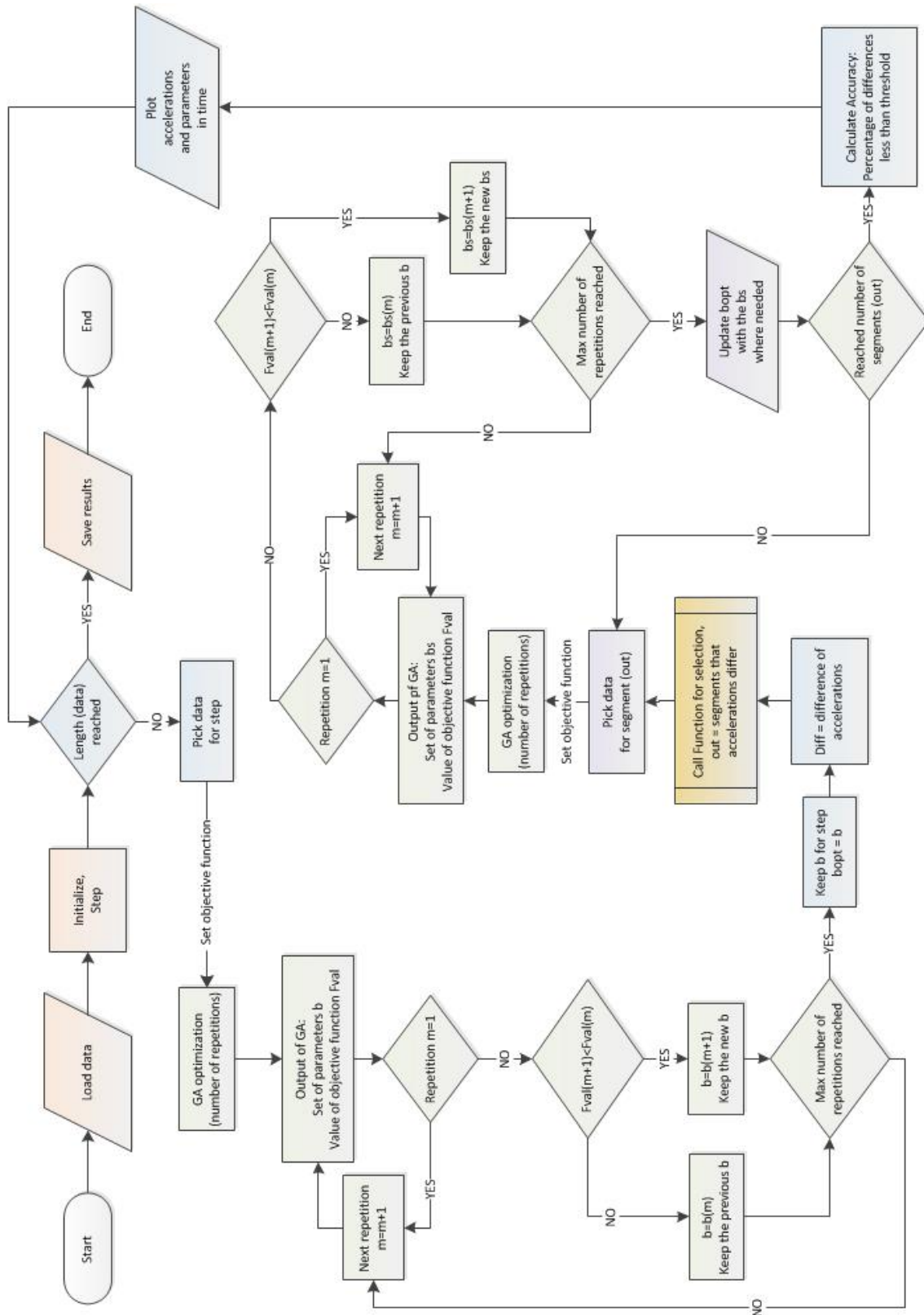
Figure A.1: Analytic flow chart of the parameter estimation model (with the genetic algorithm).
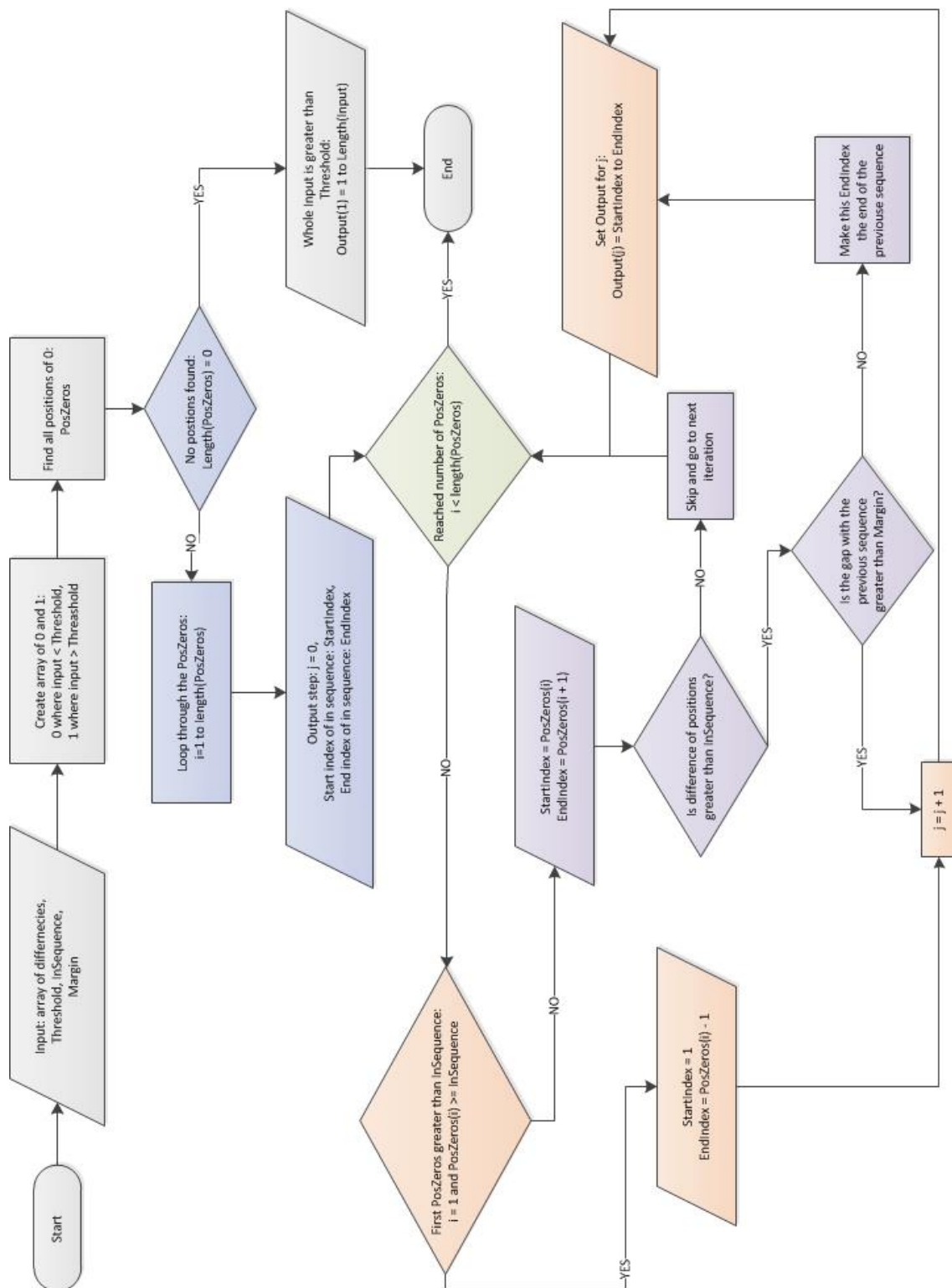
Figure A.2: Flow chart of the selection procedure of the problematic parts.

Appendix B

Analytical estimations

All the estimation results that are presented in this Appendix are made with accuracy level 0.1 m/s^2. The optimization method is the genetic algorithm with 1000 generations and 30 repetitions (Table B.1). The results of the experiment with the ACC and driver for the two data sets (7 and 8) which are valid, are given in Chapter 5. Then, the estimation results from the experiment with extreme driving conditions are presented. Only the valid data sets (Table 3.5) were used in the estimation procedure. Data sets 1 and 13 are analyzed extensively in Chapter 5.

Finally, the estimated results from the normal driving experiment are presented. The results are presented in plots of the calculated and the observed acceleration, the relative velocity, the relative distance and the steering. Also, the plots of the parameters are presented in order to observe the identified action points. Above each plot a small table with some comments on the plot is added.

Table B.1: Selected options for the data presented in the Appendix.

Options	Values
Optimization method	Genetic algorithm
Generations	1000
Repetitions of GA	30
Accuracy level	0.1 m/s^2

| Experiment	Extreme driving movement (car n)
Length	120 sec
Number of action points	1 (not identified, differences of accelerations for a limited time period < 20 sec)
0-60 sec	Secondary road, not always car in-front (identification not possible, difference in accelerations).
60-120 sec	Highway, driving with speed limit (70 km/h).
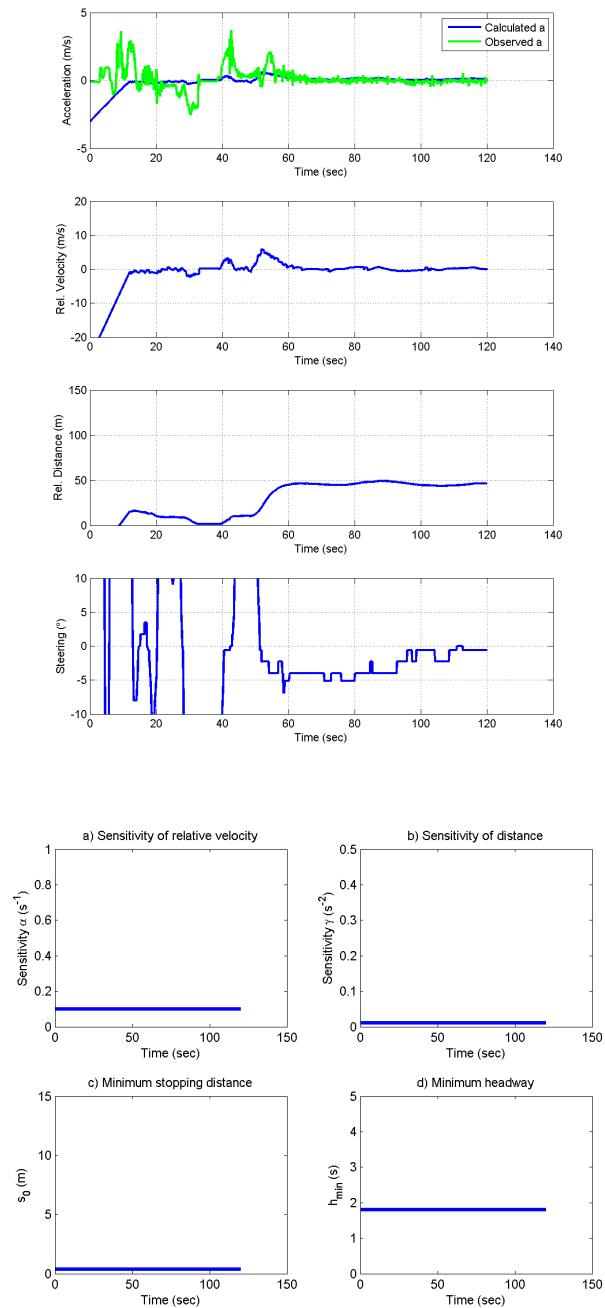
Figure B.1: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points of data set 6.

| Experiment	Extreme driving movement (car n)
Length	120 sec
Number of action points	0 (Identified)
0-120 sec	Not normal driving of car n. Accelerates, gets closer to car n+1, then decelerates by releasing the throttle. Continuous change of lanes. The continuous change of driving style (less than 20 sec) does not permit good identification.

Figure B.2: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points of data set 8.

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| Experiment	Extreme driving movement (car n)
Length	160 sec
Number of action points	0 (not identified)
0-120 sec	Change of lanes and not always car in-front.
120-160 sec	Secondary road, not always car in-front (identification not possible, difference in accelerations). The model identifies two action points in the beginning (more than 20 sec with difference of accelerations > 0.1). Driving styles change much more often but the identification is not possible.
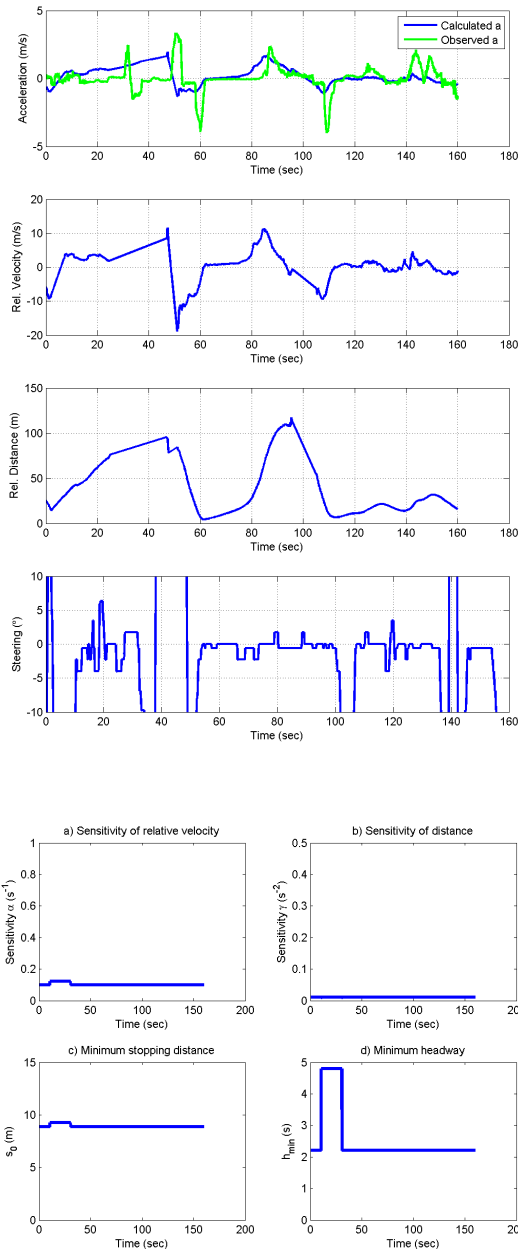
Figure B.3: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points of data set 12.

Experiment	Extreme driving movement (car n)
Length	160 sec
Number of action points	0 (Identified)
0-70 sec	Car in-front leaves lane and comes back, so not continuously car-following task.
120-150 sec	Change of lanes (identification not possible).
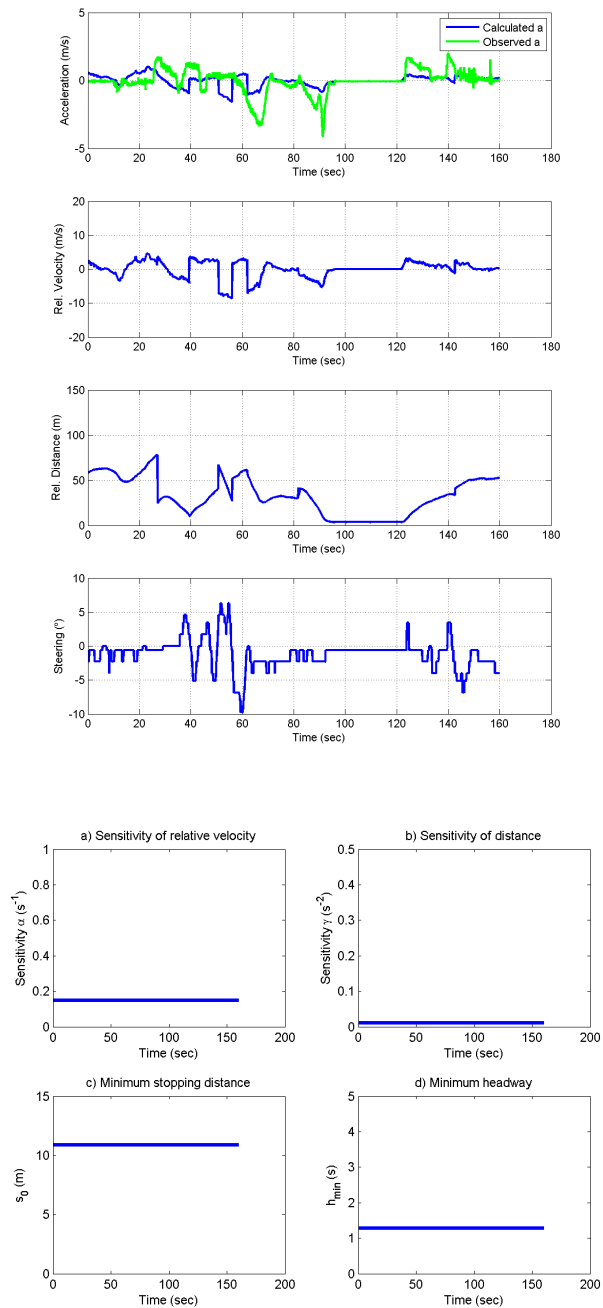
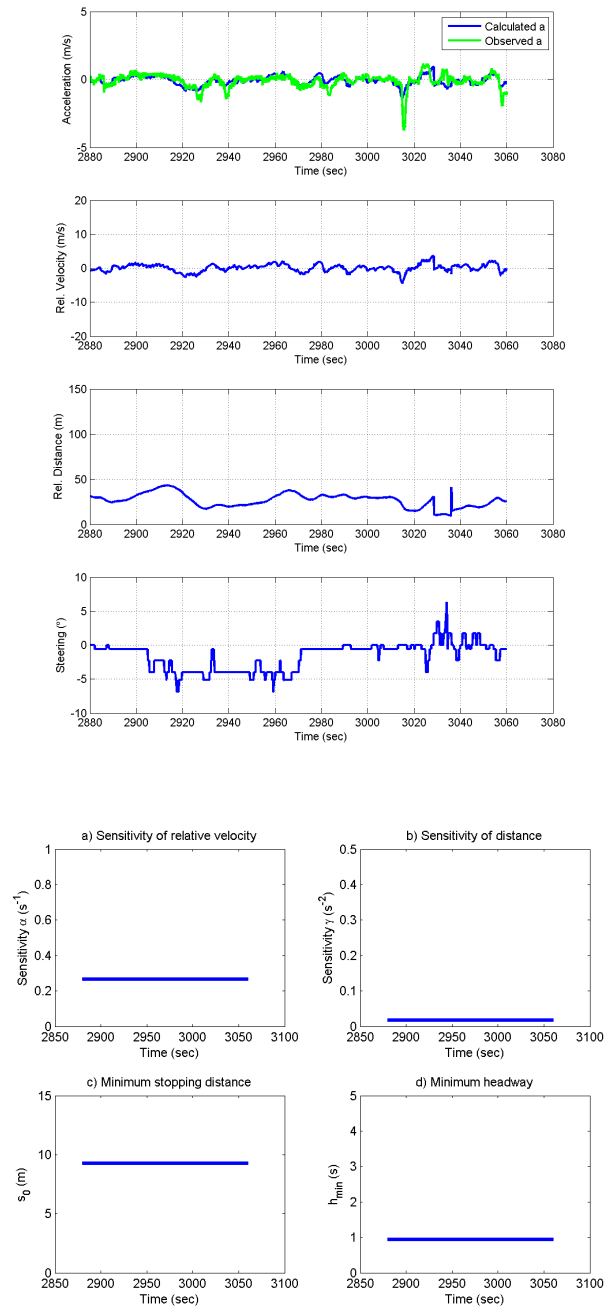Figure B.4: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points of data set 15.

| Experiment	Extreme driving movement (car n)
Length	90 sec
Number of action points	1 (not identified)
0-60 sec	Deceleration to stop in traffic light, no traffic (driver can decelerate as he wishes).
60-90 sec	Car enters secondary road (identification not possible).
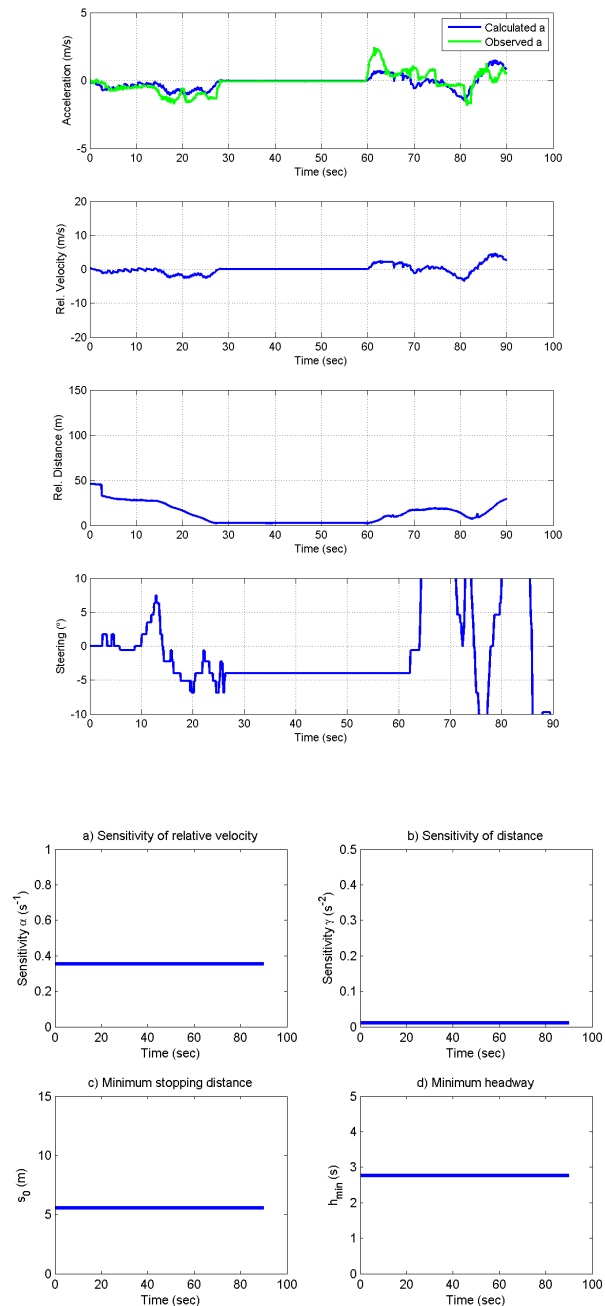
Figure B.5: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points of data set 16.

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Experiment	Normal driving 22nd October
Number of action points	0 (identified)
720-870 sec	Normal car-following, small differences due to sudden braking of car n+1.
870-900 sec	Large steering due to change of road (ring road).
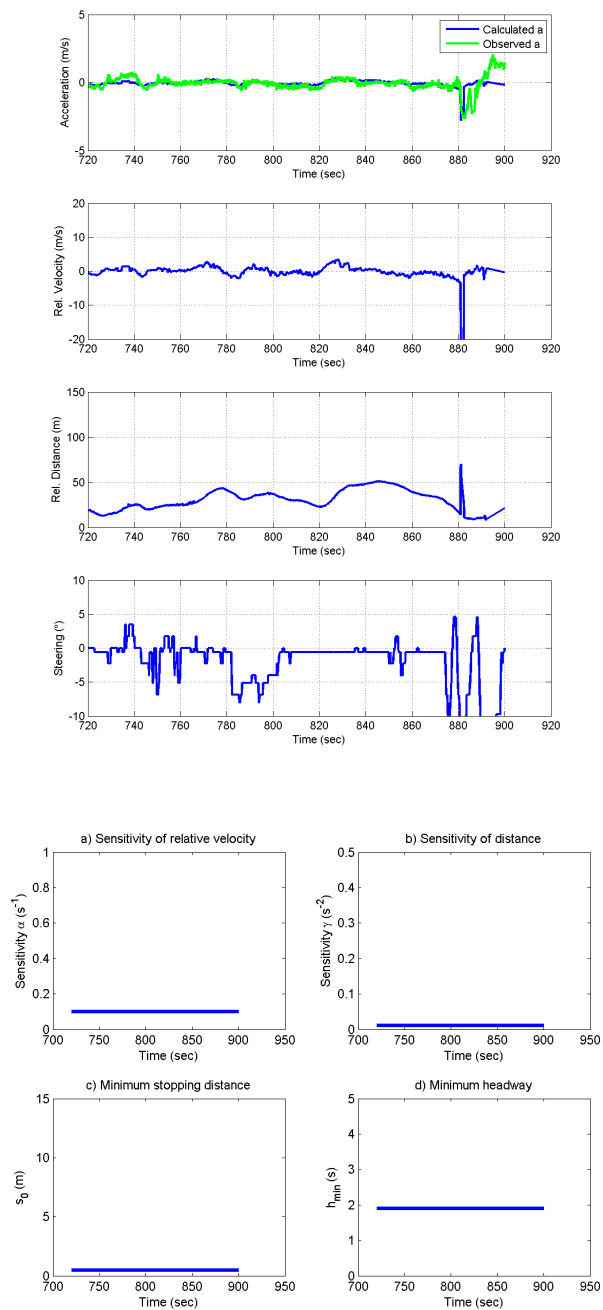
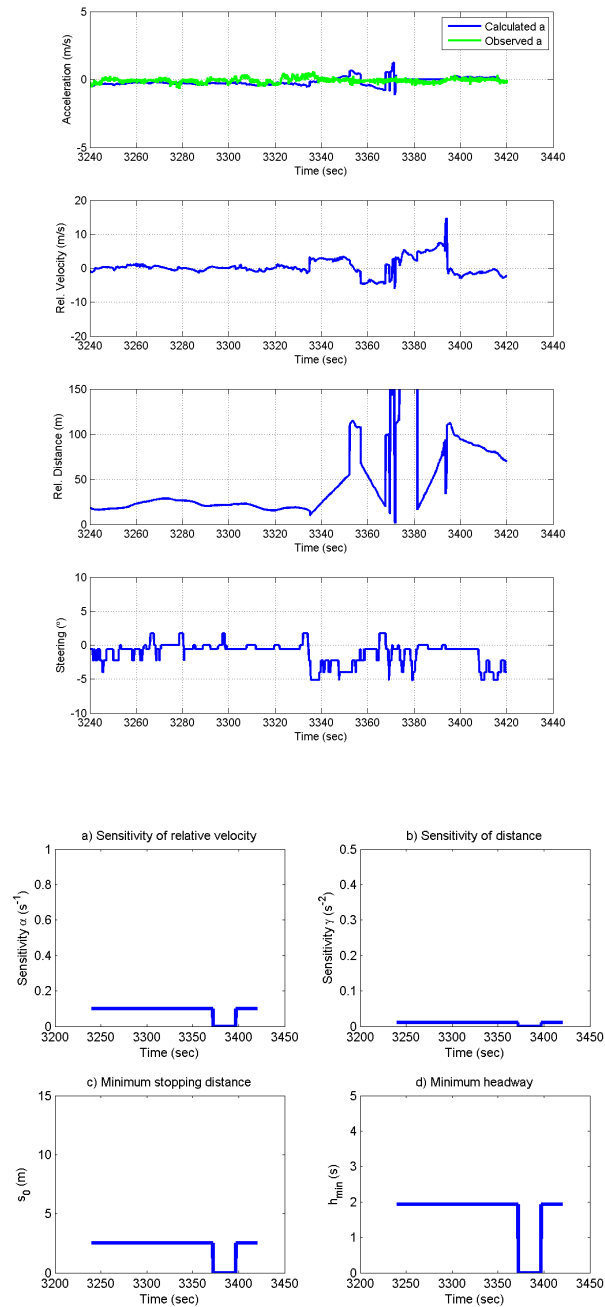Figure B.6: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points, 720-900 sec.

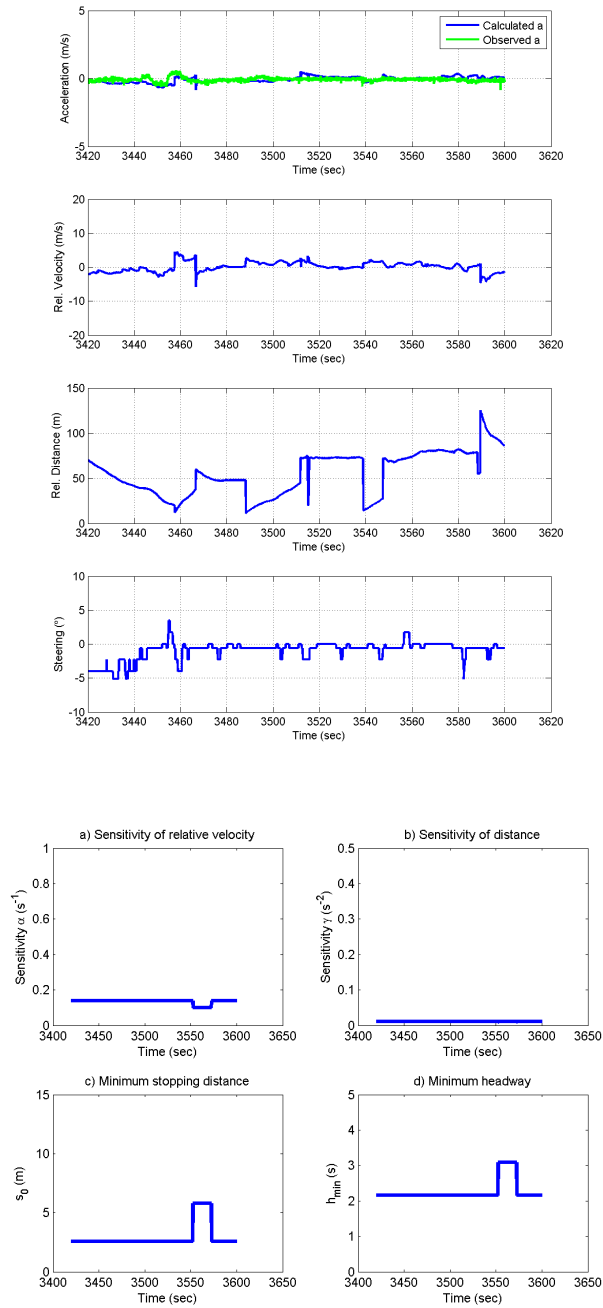| Experiment	Normal driving 22nd October
Number of action points	6 (identified)
900-930 sec	Secondary road, not always car in-front.
945-970 sec	Highway, steering and not always car in-front.
990-1030 sec	Highway, steering and not always car in-front.
All the other	Car-following.
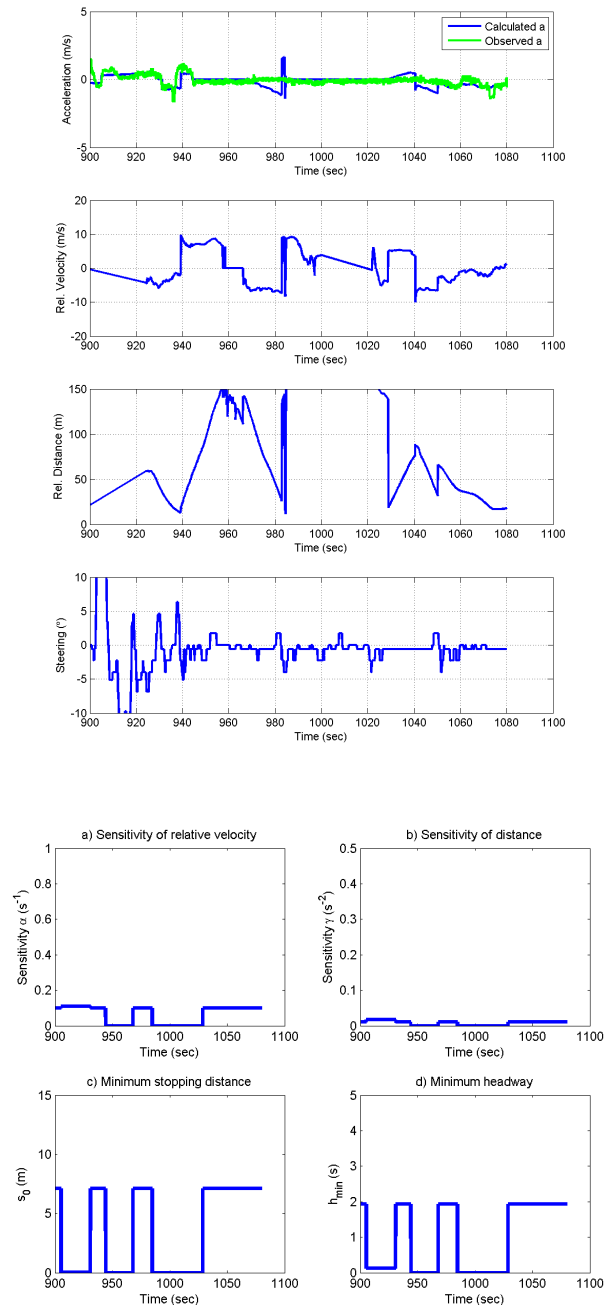
Figure B.7: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points, 900-1080 sec.

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Experiment	Normal driving 22nd October
Number of action points	2 (not identified, differences of accelerations for a limited time period < 20 sec)
1140 - 1180 sec	Steering and continuous change of lanes.
All the other	Car following, small differences due to sudden braking of car n+1.
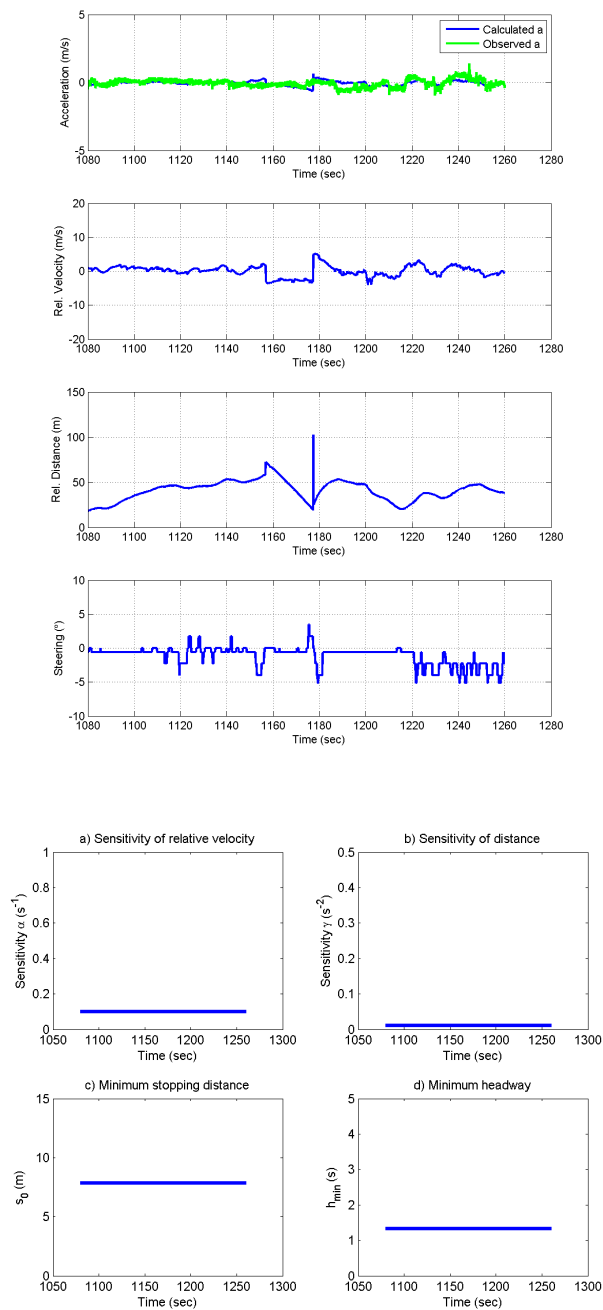
Figure B.8: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points, 1080-1260 sec.

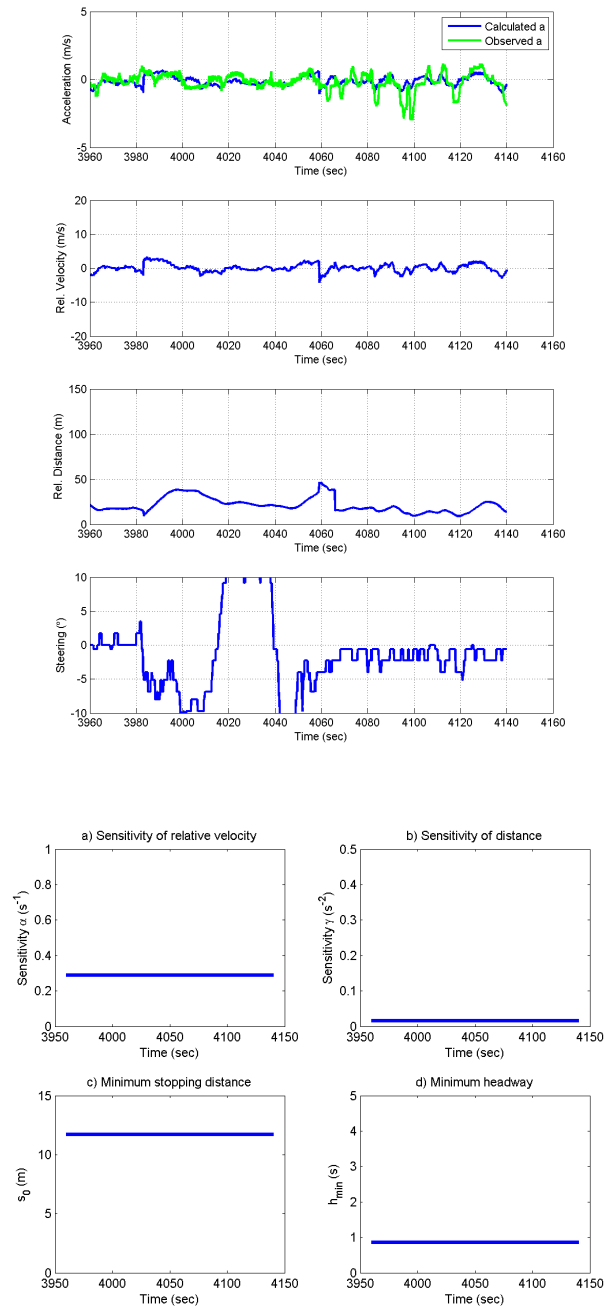| Experiment	Normal driving 22nd October
Number of action points	3 (2 identified)
1440-1460 sec	Car moves in off-ramp (not always car in-front, large steering).
1460-1480 sec	No car in-front (identified by system).
1480-1550 sec	Car-following.
1550-1620 sec	Large steering and no car in-front.
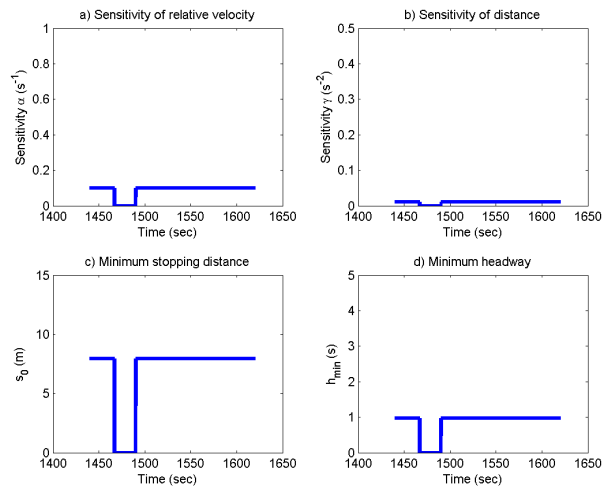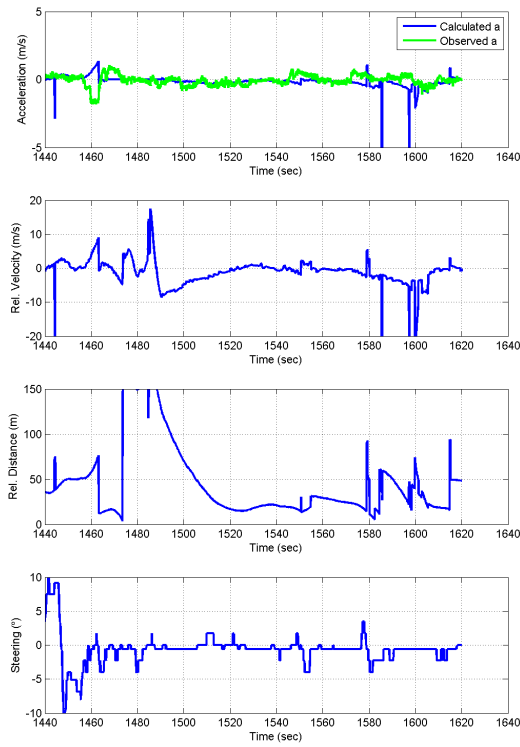
Figure B.9: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points, 1440-1620 sec.

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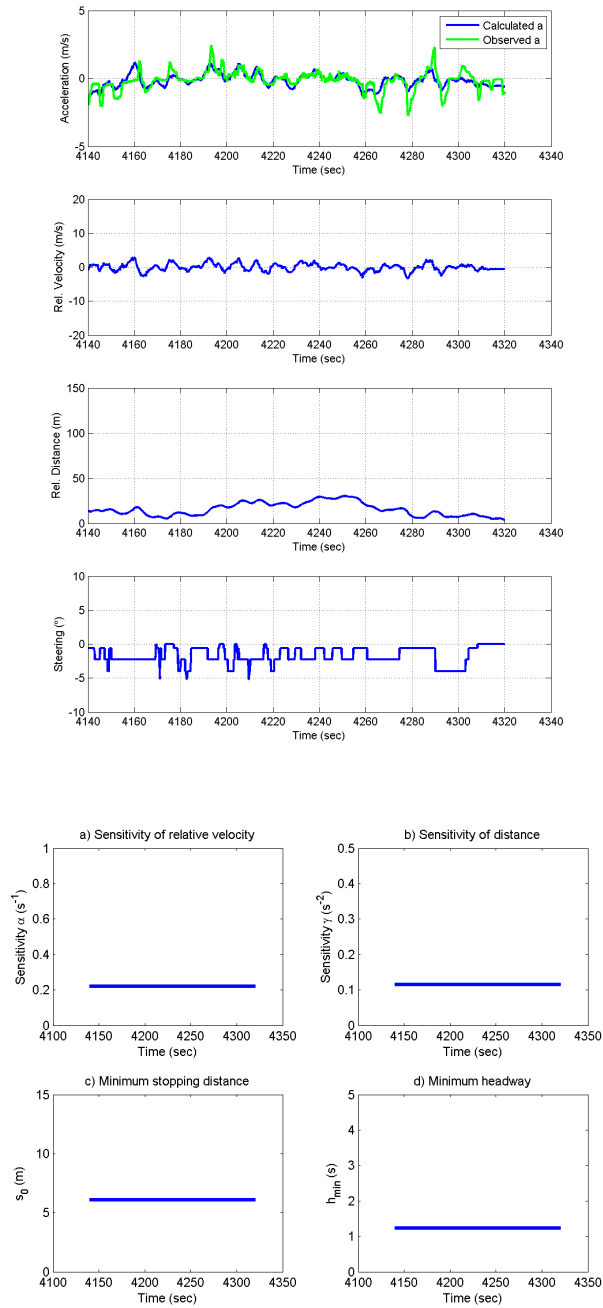| Experiment	Normal driving 22nd October
Number of action points	0 (identified)
All	Car-following.
Small differences	Change of car in-front or change of lane.

Figure B.10: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points, 1620-1800 sec.

Experiment	Normal driving 22nd October
Number of action points	0 (identified)
All	Car-following.
1920-1980 sec	There is an on-ramp, but no effect in driver is identified. Also car n+1 changes lanes, distance with car n+2 very small and that is why no effect in driving behavior.
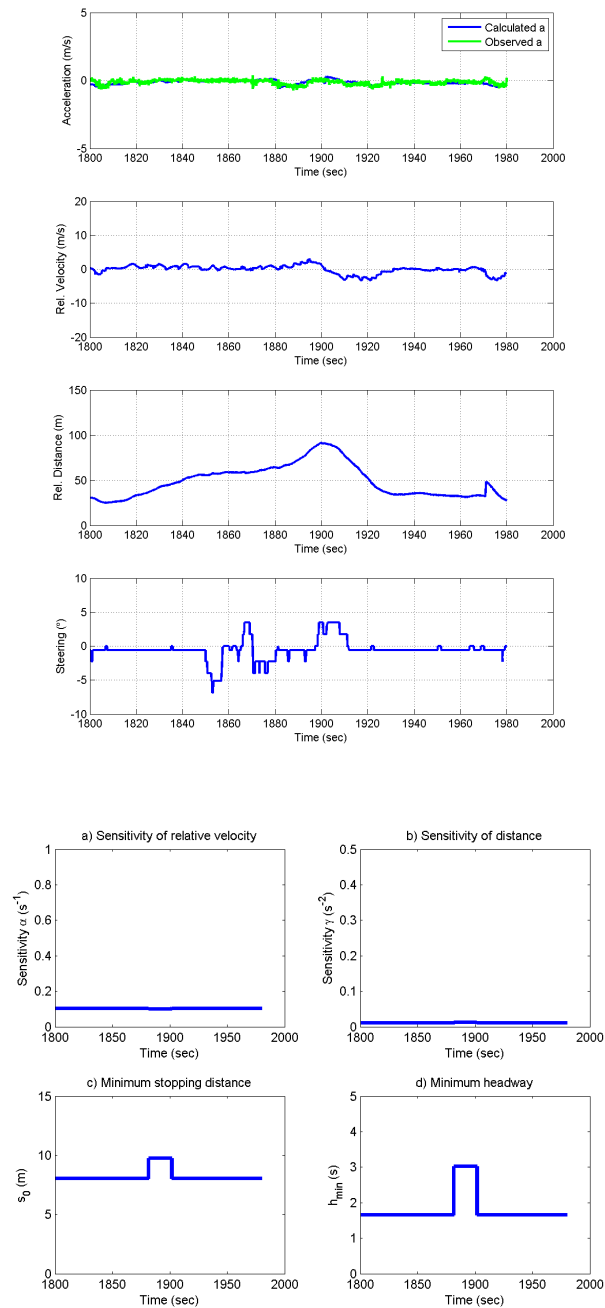
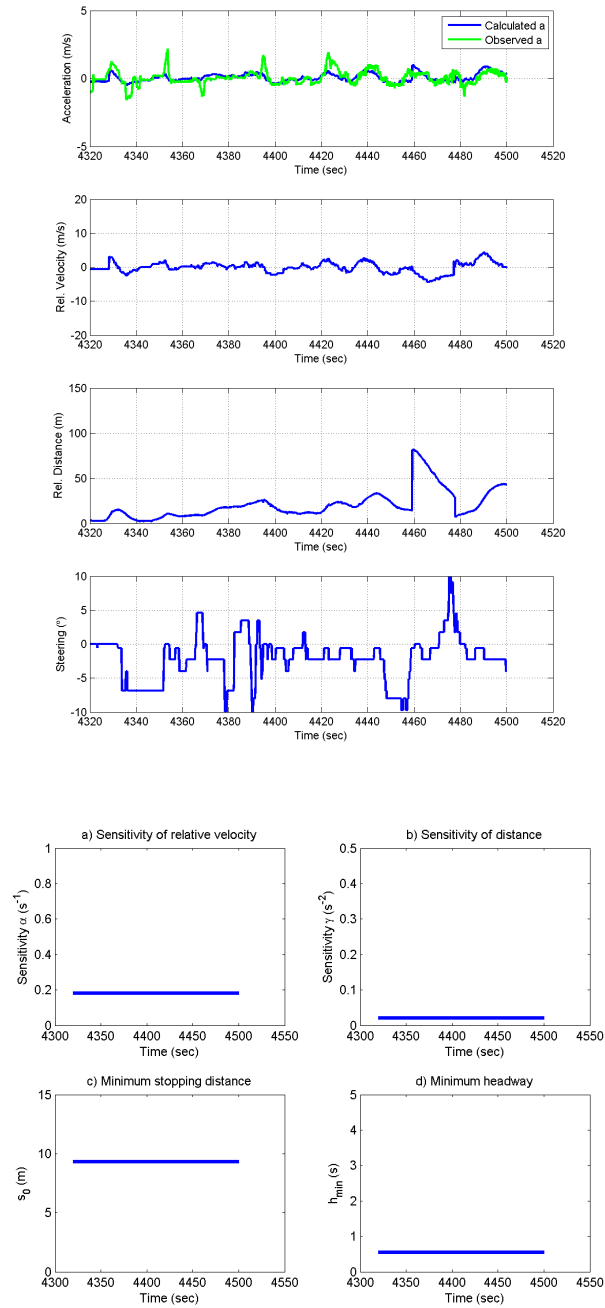Figure B.11: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points, 1800-1980 sec.

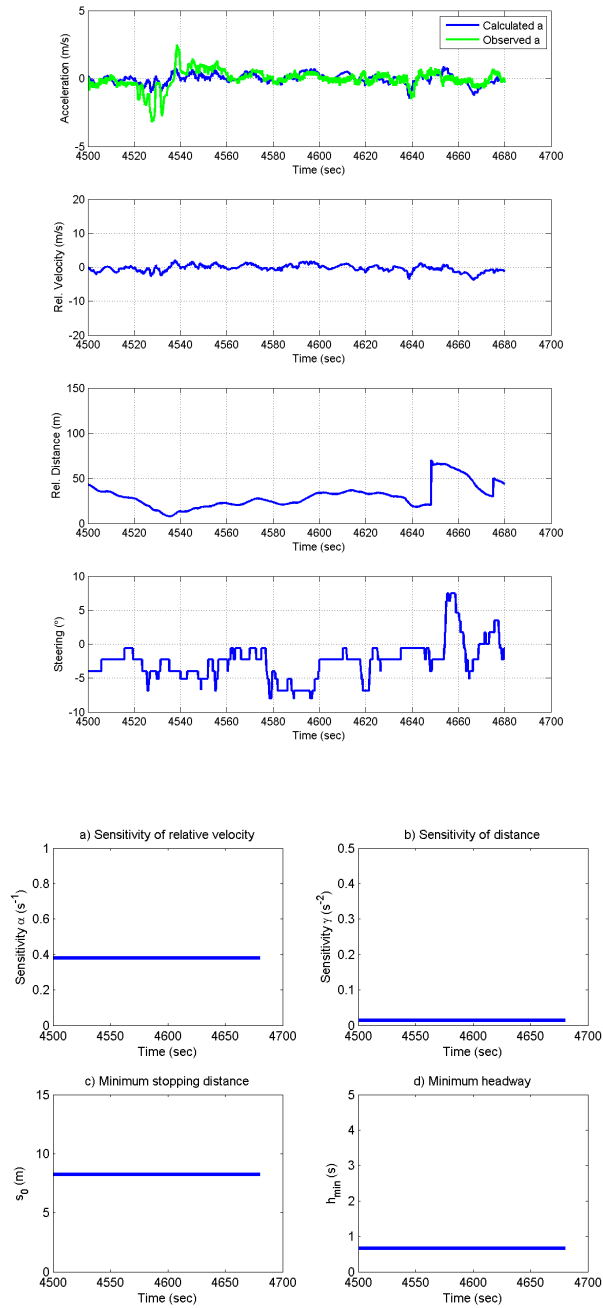| Experiment	Normal driving 22nd October
Number of action points	4 (2 identified)
2180-2210 sec	Change of lanes (not same conditions in next lane), captured by second estimation.
2240-2270 sec	Braking of car n+1 and small relative distance.
All the other	Car-following.
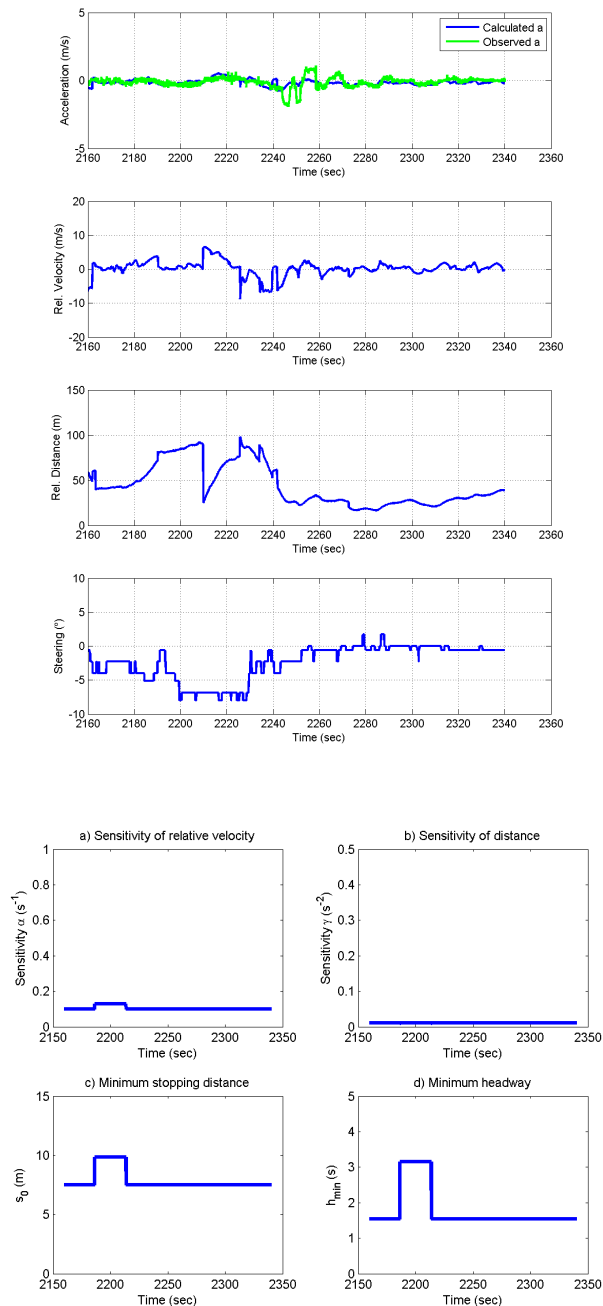
Figure B.12: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points, 2160-2340 sec.

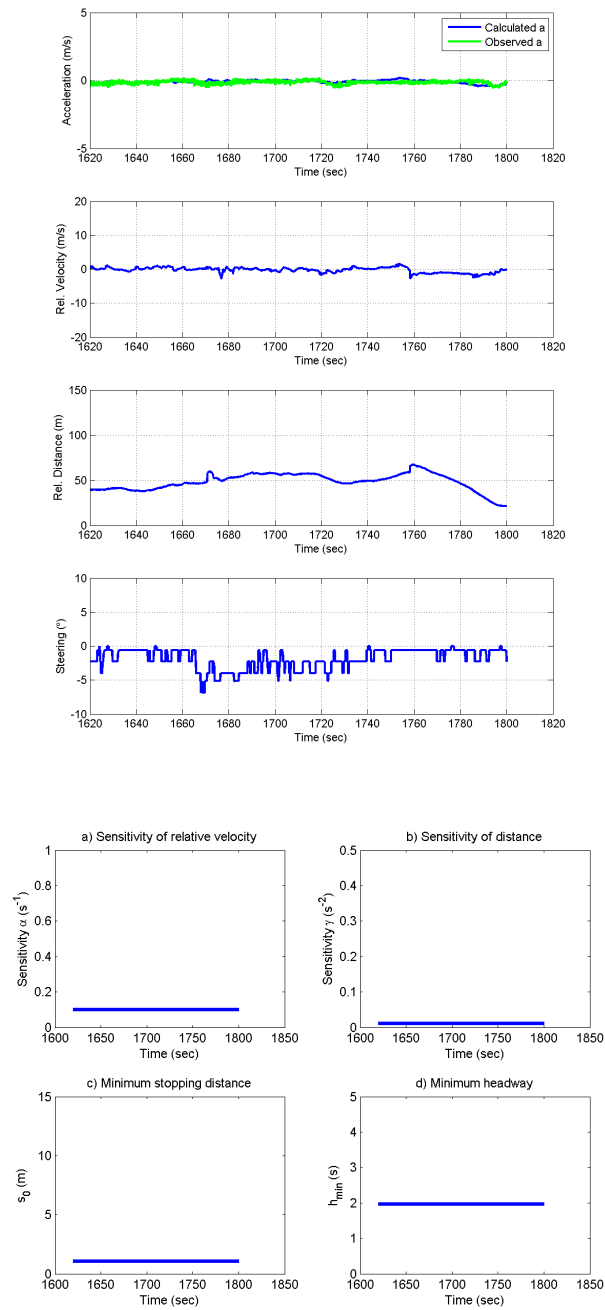| Experiment	Normal driving 22nd October
Number of action points	2 (not identified)
2520-2650 sec	Continuous change of lanes, and relative distance > 100 m.
2650-2680 sec	Car-following.
2680-2700 sec	Braking of car n+1.
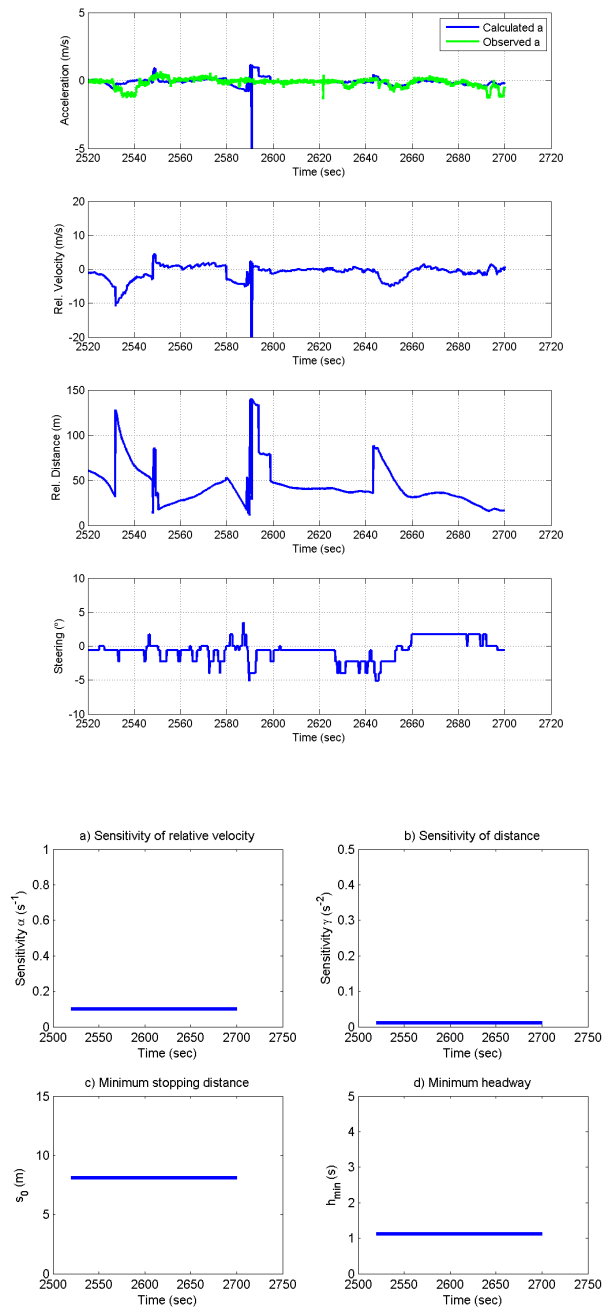
Figure B.13: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points, 2160-2340 sec.

Experiment	Normal driving 22nd October
Number of action points	0 (identified)
2720, 2745, 2800, 2865 sec	Braking of car n+1 and relative distance < 50 m.
All the other	Car following (even in sharp curves estimation possible due to small relative distance).
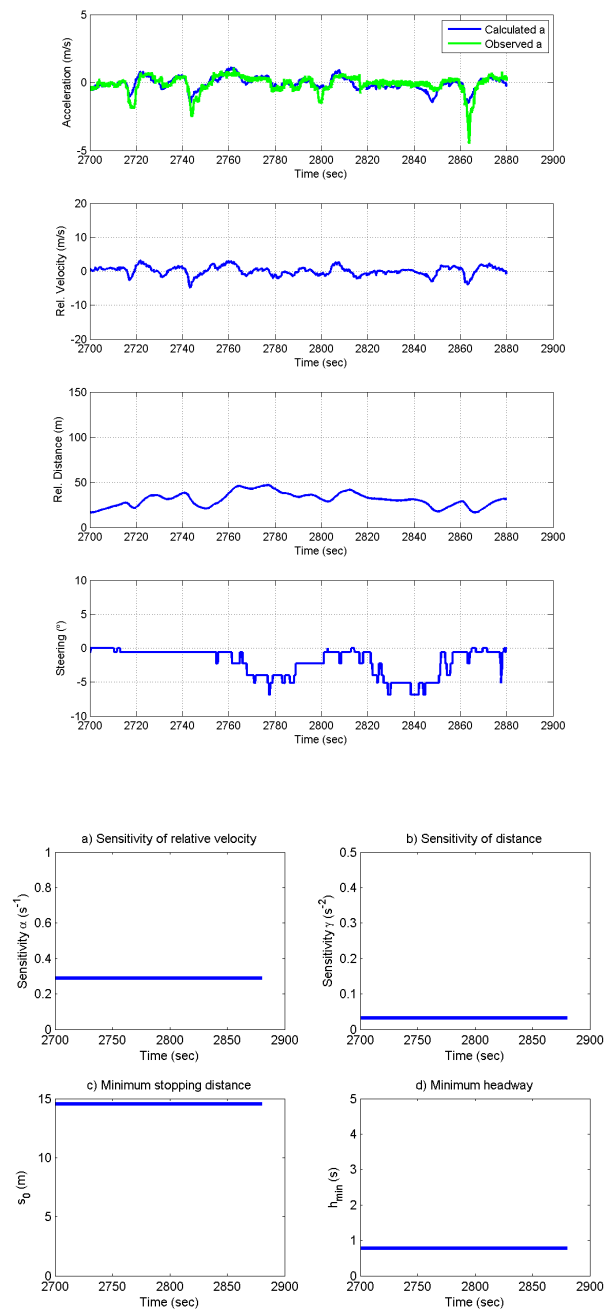
Figure B.14: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points, 2700-2880 sec.

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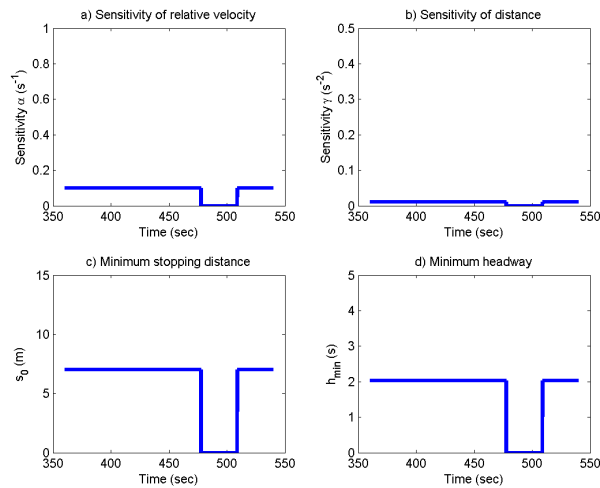| Experiment	Normal driving 22nd October
Number of action points	0 (identified)
2930, 2940, 3015 sec	Braking of car n+1 and relative distance < 50 m.
All the other	Car following.

Figure B.15: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points, 2880-3060 sec.

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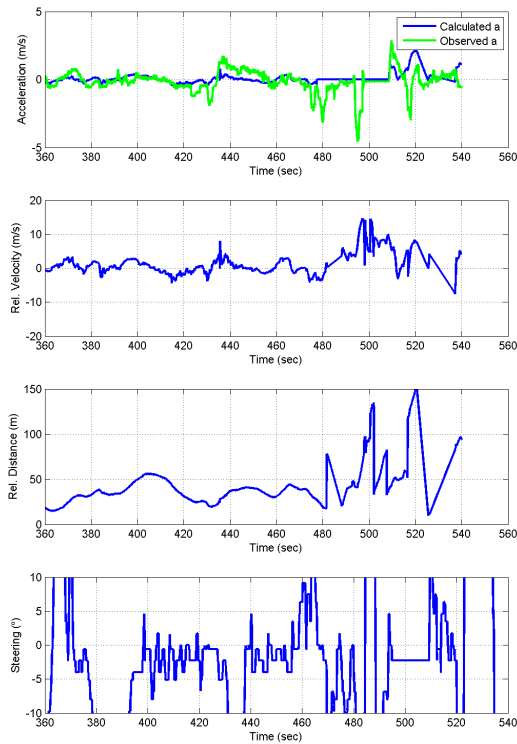| Experiment	Normal driving 22nd October
Number of action points	0 (identified)
3100-3120 sec	Car n+1 leaves to off-ramp, no car in-front for a while.
3190-3210 sec	Truck in position n+1 and lots of traffic.
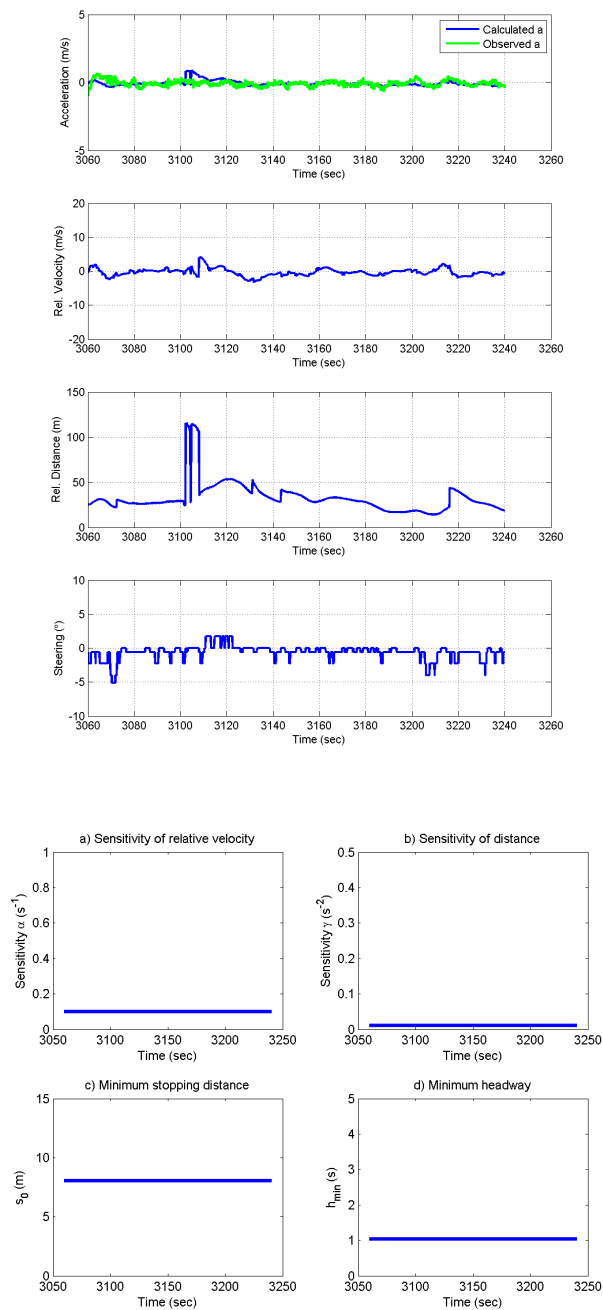
Figure B.16: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points, 3060-3240 sec.

Experiment	Normal driving 22nd October
Number of action points	2 (identified)
3360-3380 sec	Overtaking of the car in-front.
All the other	Car-following.

Figure B.17: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points, 3240-3420 sec.

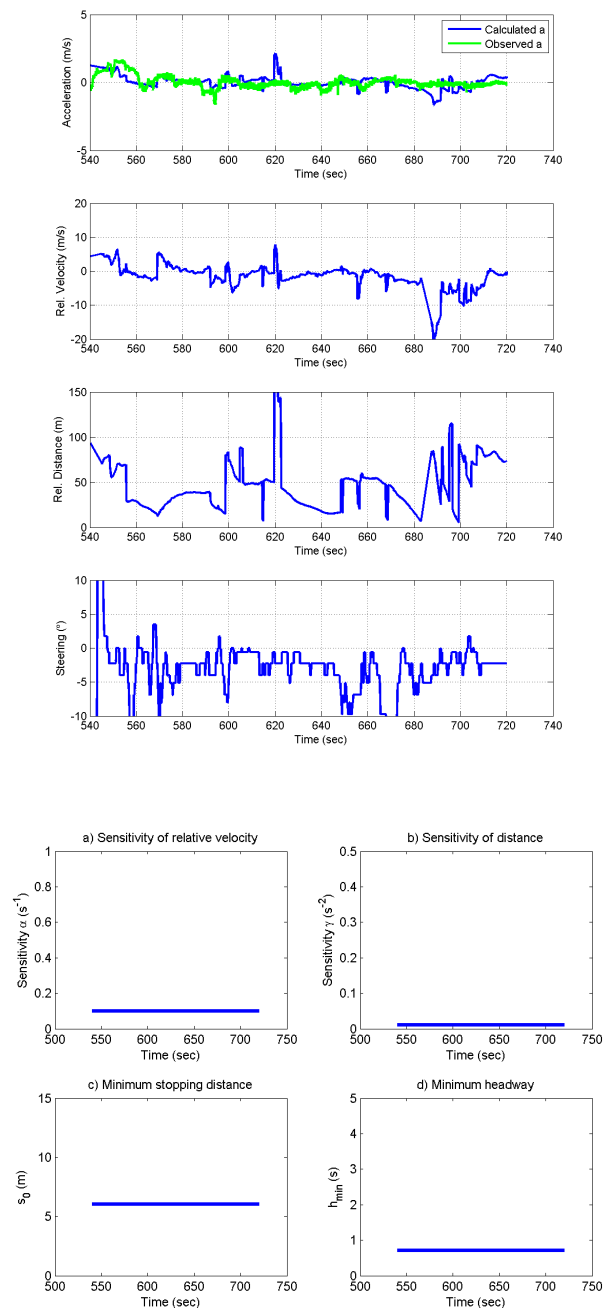| Experiment	Normal driving 22nd October
Number of action points	0 (identified)
All	Car-following.

Figure B.18: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points, 3420-3600 sec.

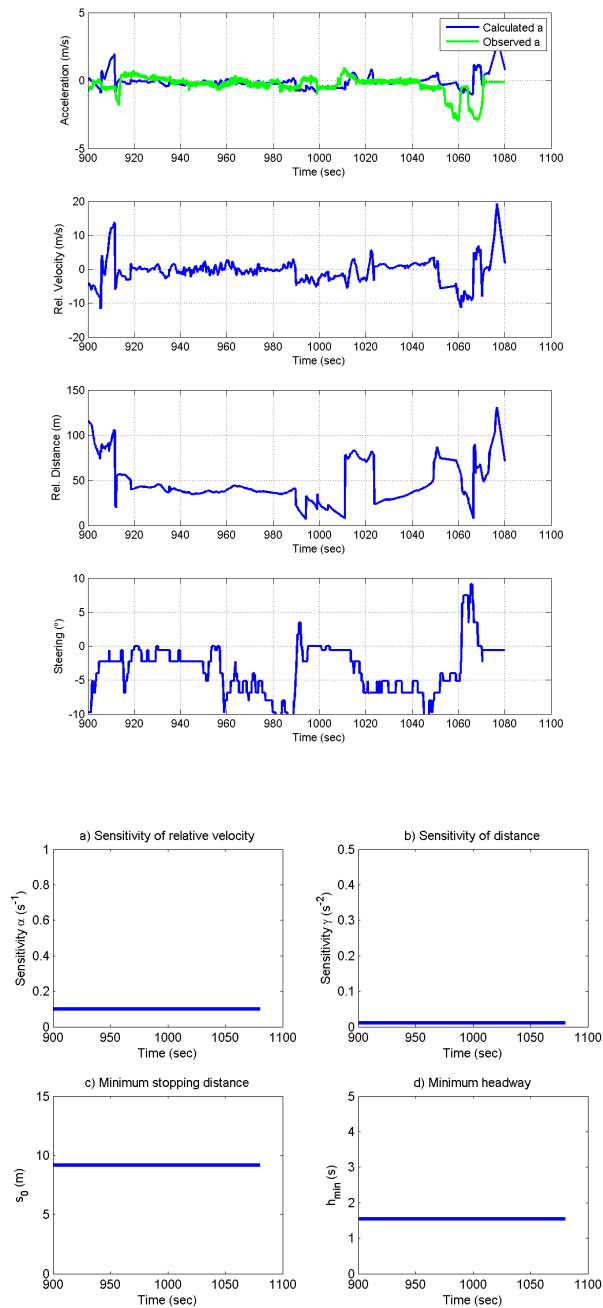| Experiment	Normal driving 22nd October
Number of action points	0 (identified)
All	Car-following (small differences due to braking of car n+1).
4010-4040 sec	Steering due to very sharp curve, but relative distance small, so system works fine.

Figure B.19: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points, 3960-4140 sec.

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Experiment	Normal driving 22nd October
Number of action points	0 (identified)
All	Car-following, stop and go wave (small differences due unexpected braking of car n+1).

Figure B.20: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points, 4140-4320 sec.

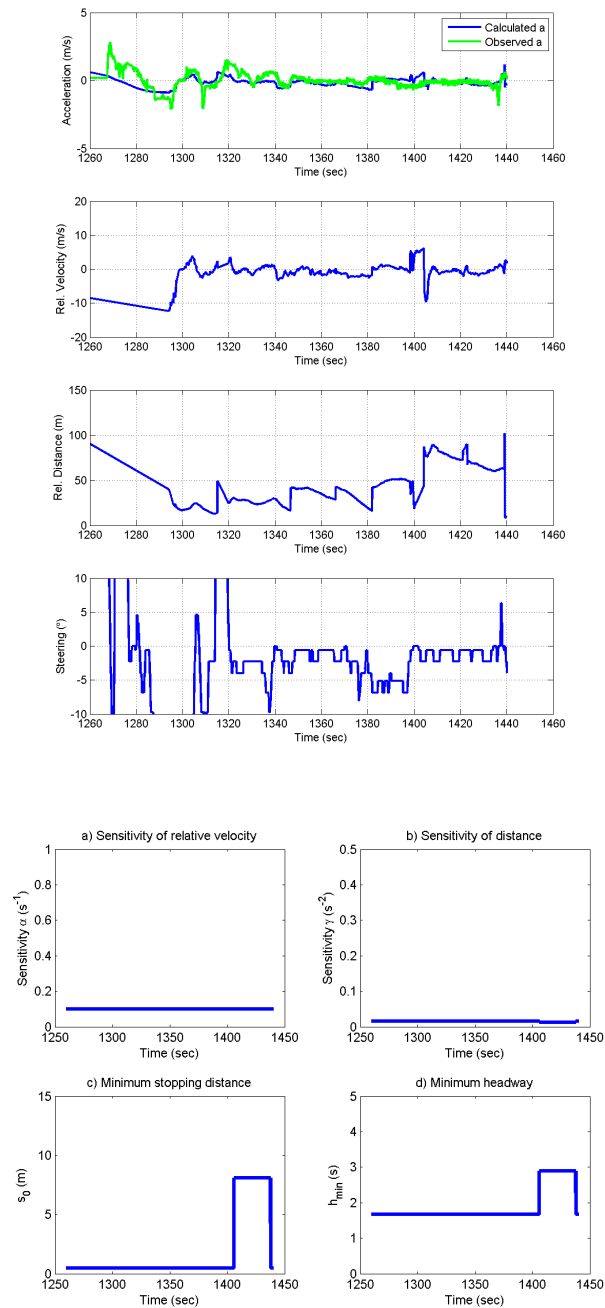| Experiment	Normal driving 22nd October
Number of action points	0 (identified)
All	Car-following (small differences due unexpected braking of car n+1).

Figure B.21: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points, 4320-4500 sec.

Experiment	Normal driving 22nd October
Number of action points	0 (identified)
All	Car-following (small differences due unexpected braking of car n+1).

Figure B.22: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points, 4500-4680 sec.

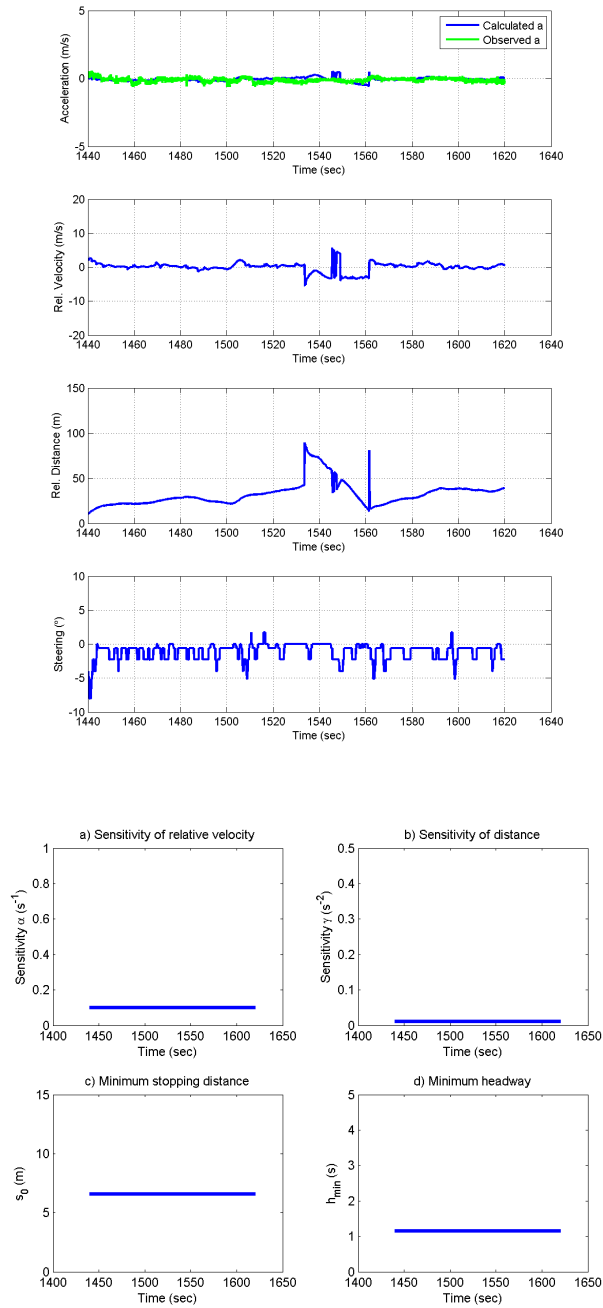| Experiment	Normal driving 23rd October, morning
Number of action points	0 (identified)
All	Car-following.

Figure B.23: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points, 1620-1800 sec.

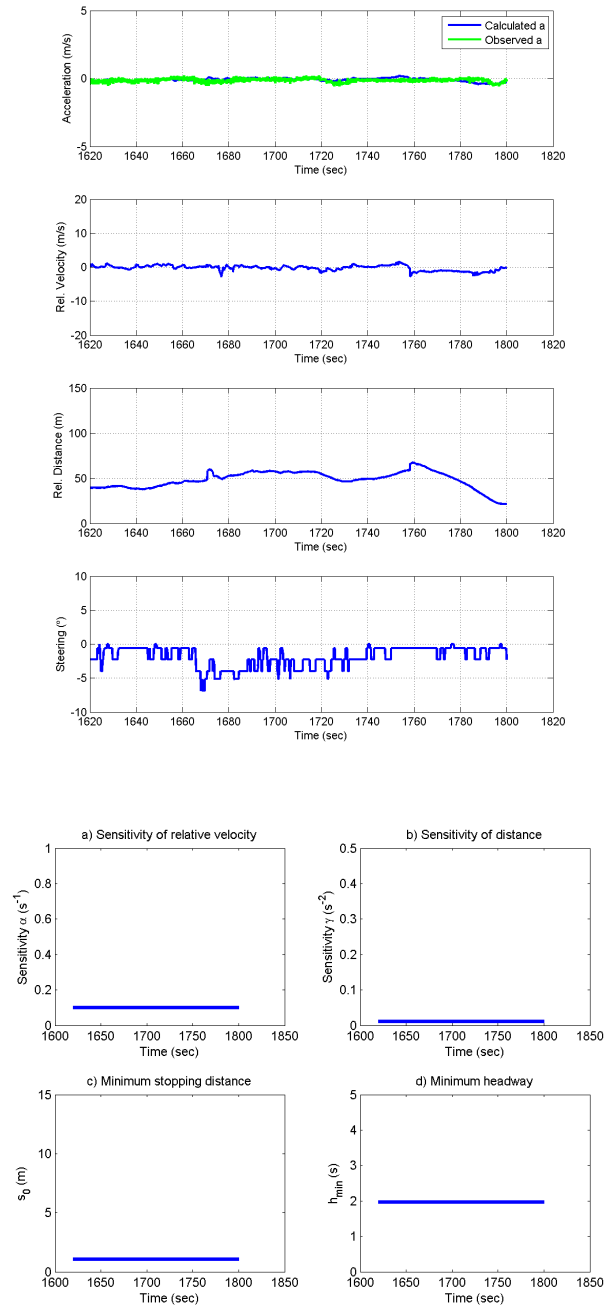| Experiment	Normal driving 23rd October, evening
Number of action points	3 (2 identified)
360-425 sec	Truck in the position n+1 (estimation is fine).
425-445 sec	Overtaking of truck.
470-510 sec	Decelerates to traffic light, but there is traffic.
510-520 sec	Change of road and style.

Figure B.24: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points, 360-540 sec.

Experiment	Normal driving 23rd October, evening
Number of action points	0 (identified)
All	Car-following task.
	Traffic in the road, forces the car-to stop and go wave. Not always possible the estimation, due to continuous braking of car n+1.

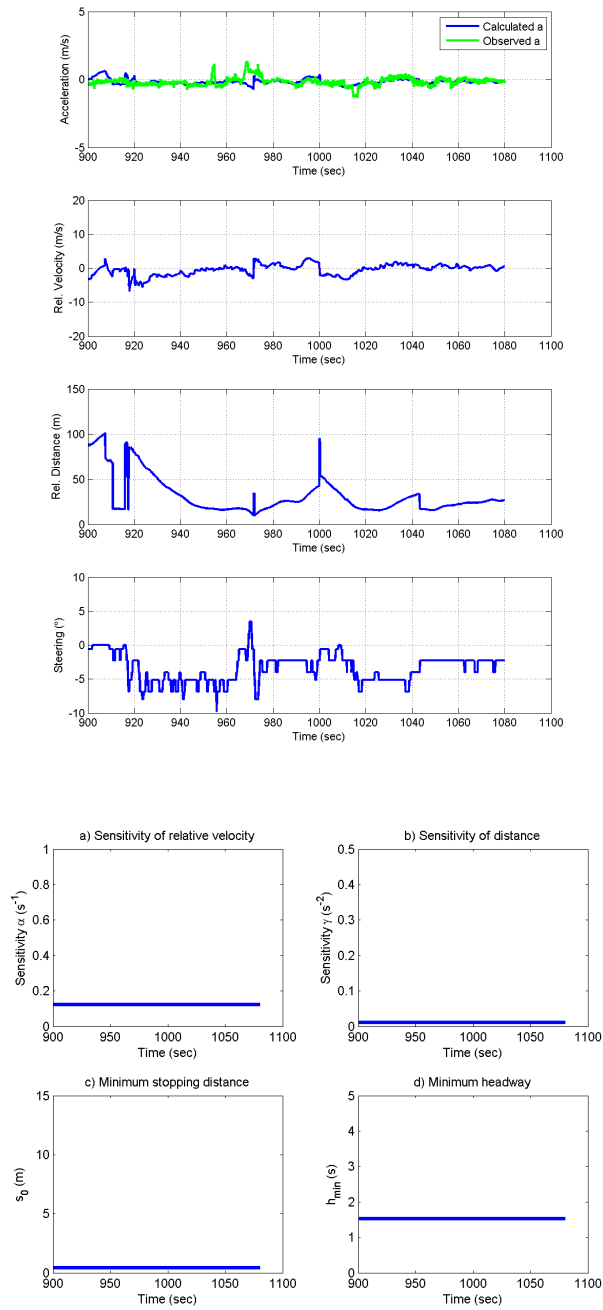Figure B.25: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points, 540-720 sec.

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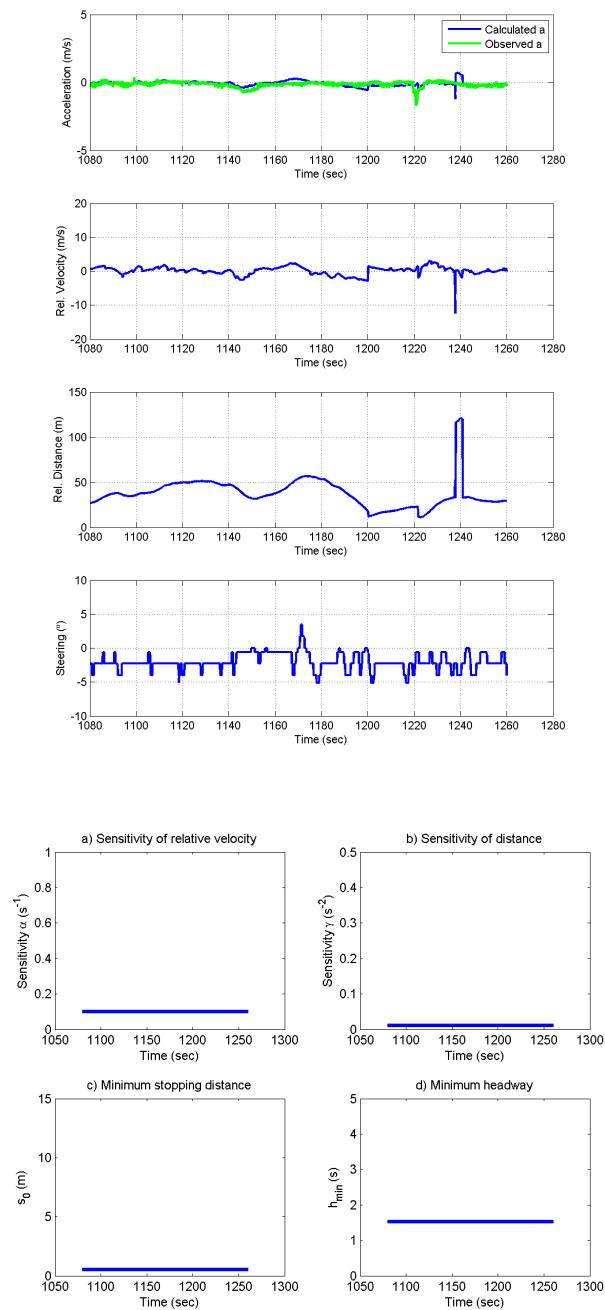| Experiment	Normal driving 23rd October, evening
Number of action points	0 (identified)
All	Car-following task.
	The car moves in secondary roads and changes from one road section to another.
	Small change of styles in every change of road.

Figure B.26: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points, 900-1080 sec.

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Experiment	Normal driving 23rd October, evening
Number of action points	3 (2 identified)
1260-1280 sec	Large curves in the road.
1410-1440 sec	The truck accelerates and there is a larger relative distance, different style of car n.
All the other	Truck-following task (small difference due to truck braking and bad visibility).

Figure B.27: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points, 1260-1440 sec.

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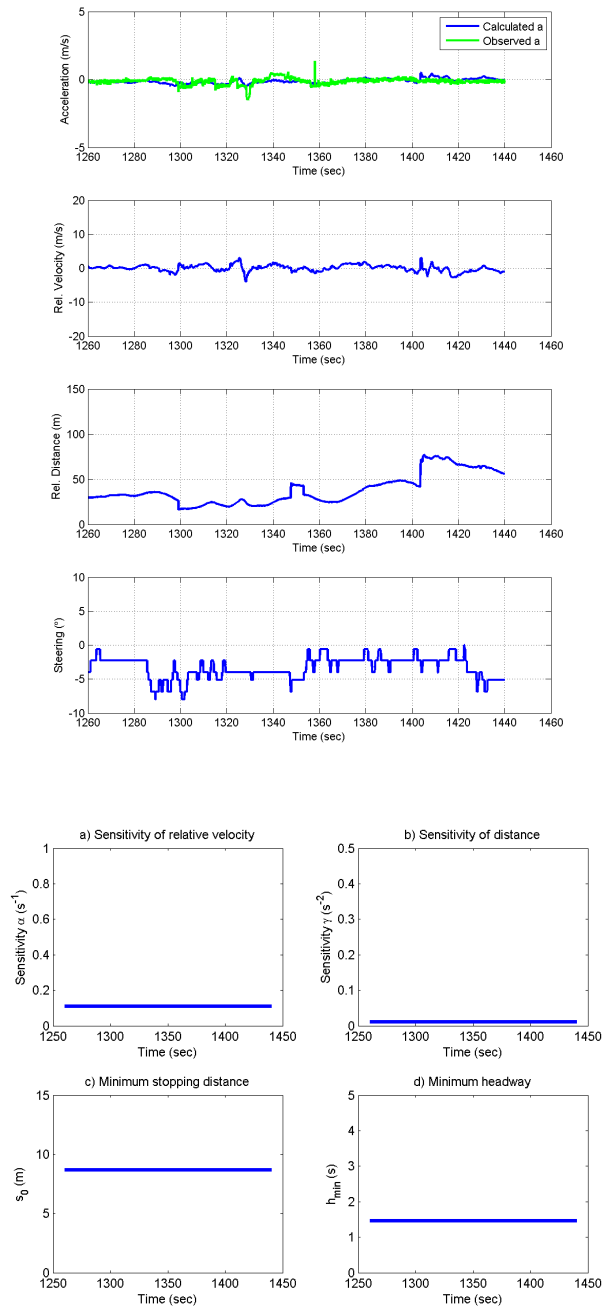| Experiment	Normal driving 23rd October, evening
Number of action points	0 (identified)
All	Truck-following task (small difference due to truck braking and bad visibility).

Figure B.28: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points, 1440-1620 sec.

Experiment	Normal driving 23rd October, evening
Number of action points	0 (identified)
All	Truck-following task (small difference due to truck braking and bad visibility).

Figure B.29: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points, 1620-1800 sec.

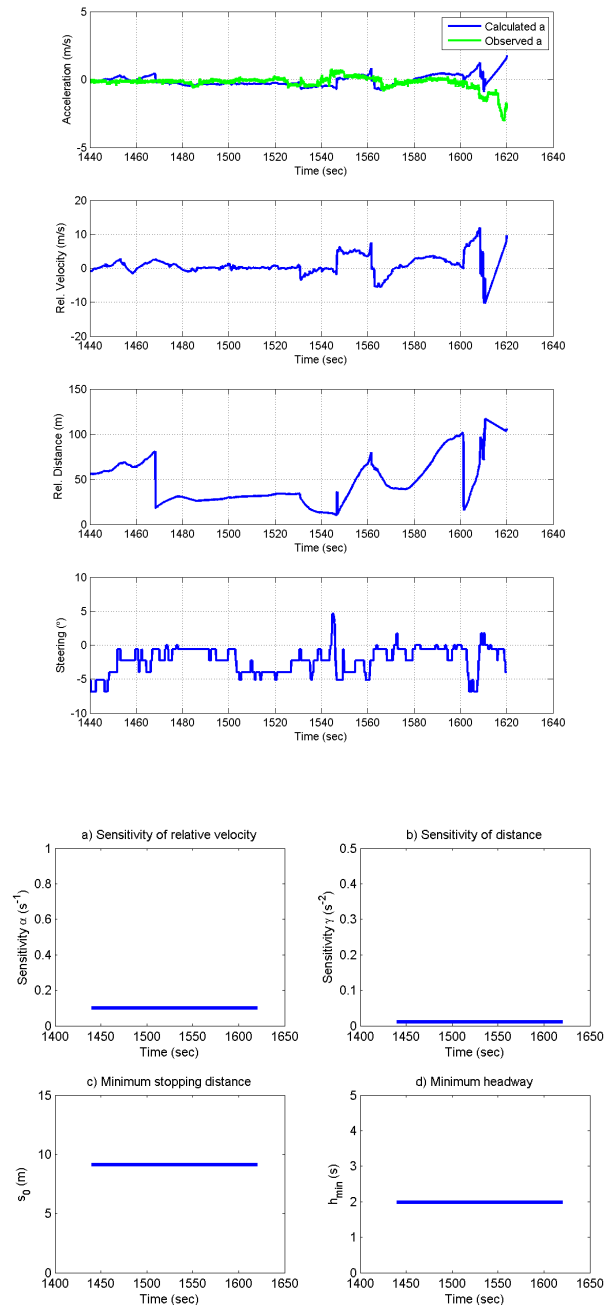| Experiment	Normal driving 24$^{\text{rd}}$ October
Number of action points	3 (not identified)
915, 970, 1010 sec	Change of lanes.
All the other	Car-following.

Figure B.30: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points, 900-1080 sec.

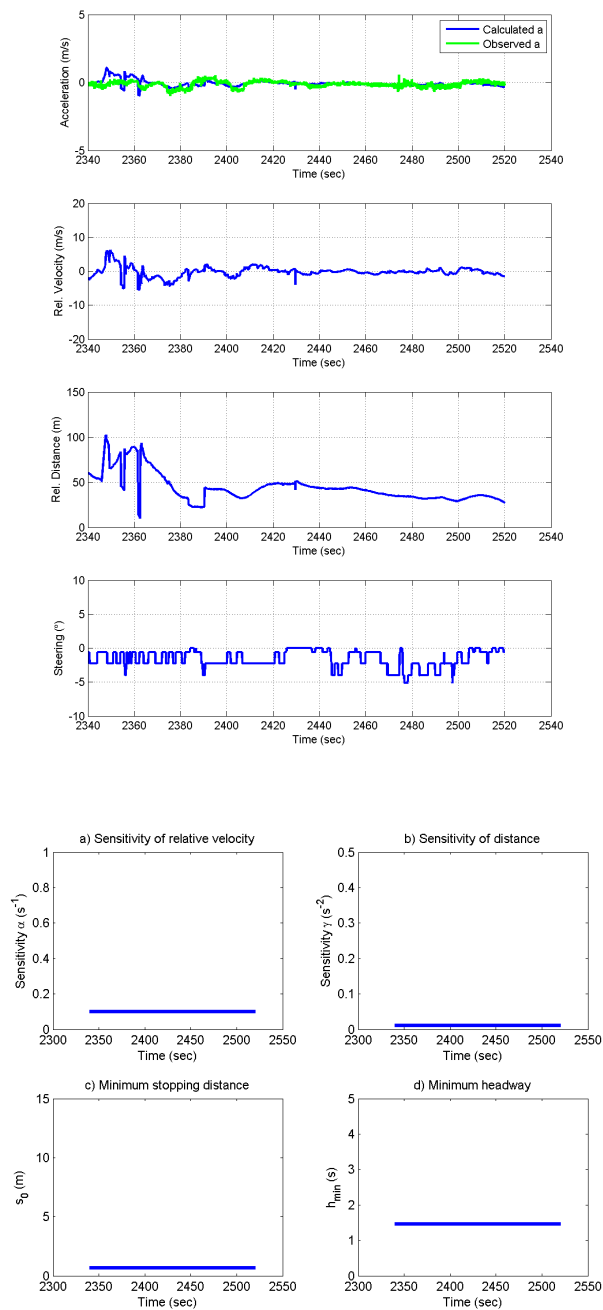| Experiment	Normal driving 24rd October
Number of action points	3 (not identified)
1170, 1200, 1240 sec	Change of lanes.
All the other	Car-following.

Figure B.31: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points, 1080-1260 sec.

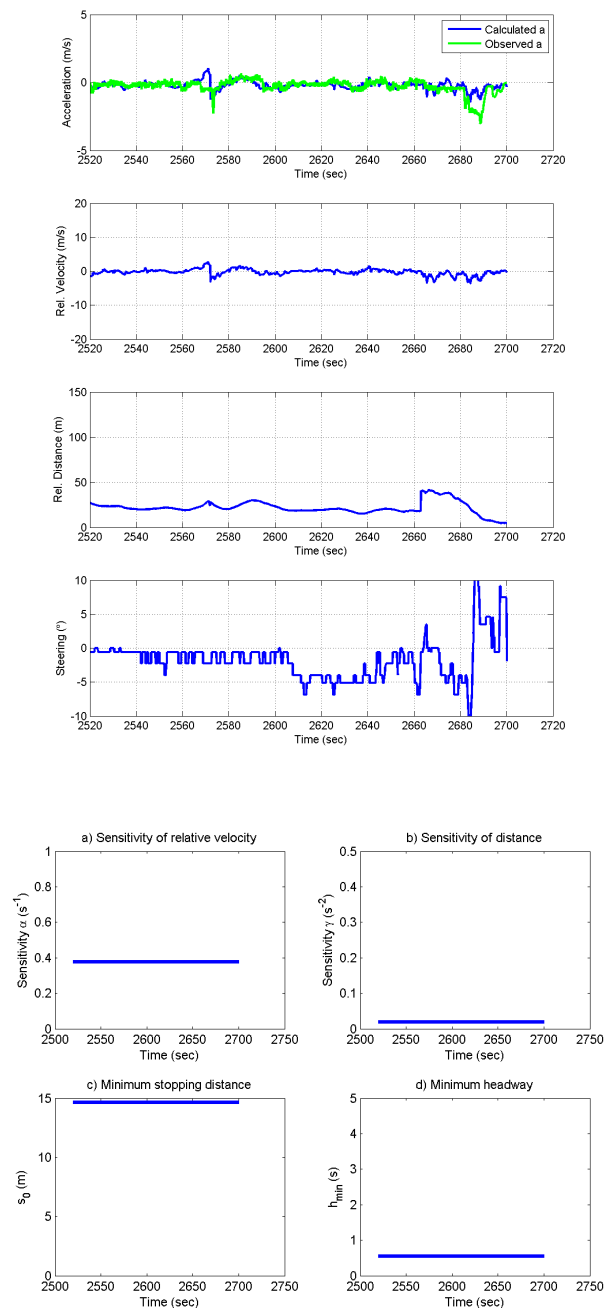| Experiment	Normal driving 24rd October
Number of action points	3 (not identified)
1280-1300 sec	Sharp curve and change of lanes.
1310 sec	A small mismatch due to braking of car n+1.
1400-1440 sec	Car in-front leaves lane and there is not a car-following task anymore.
All the other	Car-following.

Figure B.32: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points, 1260-1440 sec.

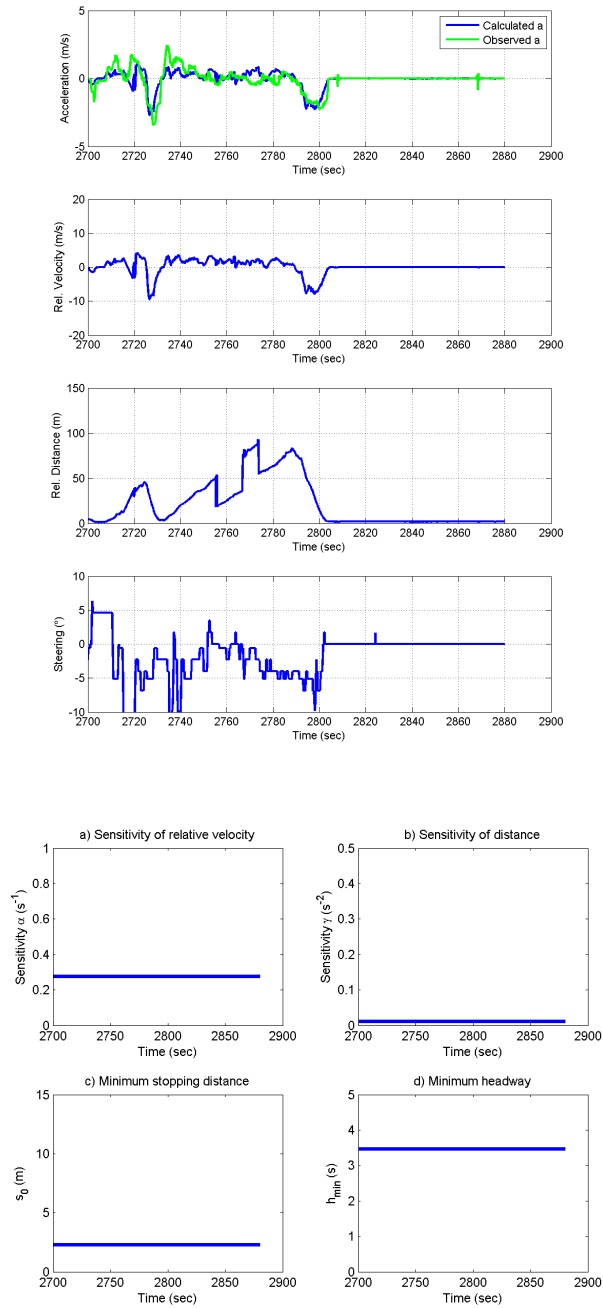| Experiment	Normal driving 24rd October
Number of action points	3 (not identified)
1440-1460 sec	Car n+1 accelerates very much and relative distance changes significantly.
1540-1560 sec	Truck gets in position n+1 and the driver changes lane.
1590-1620 sec	Car moves to an off-ramp with no car in-front.
All the other	Car-following.

Figure B.33: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points, 1440-1620 sec.

Experiment	Normal driving 24rd October
Number of action points	1 (not identified)
2340-2380 sec	Car enters in position n+1 and then leaves and the same with another car.
All the other	Car-following.

Figure B.34: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points, 2340-2520 sec.

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Experiment	Normal driving 24rd October
Number of action points	1 (not identified)
2570	A small mismatch due to sharp curve.
2680-2700	The car leaves the highway and moves to an off-ramp.
All the other	Car-following.

Figure B.35: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points, 2520-2700 sec.

Experiment	Normal driving 24rd October
Number of action points	0 (identified)
All	Car-following.

Figure B.36: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points, 2700-2880 sec.

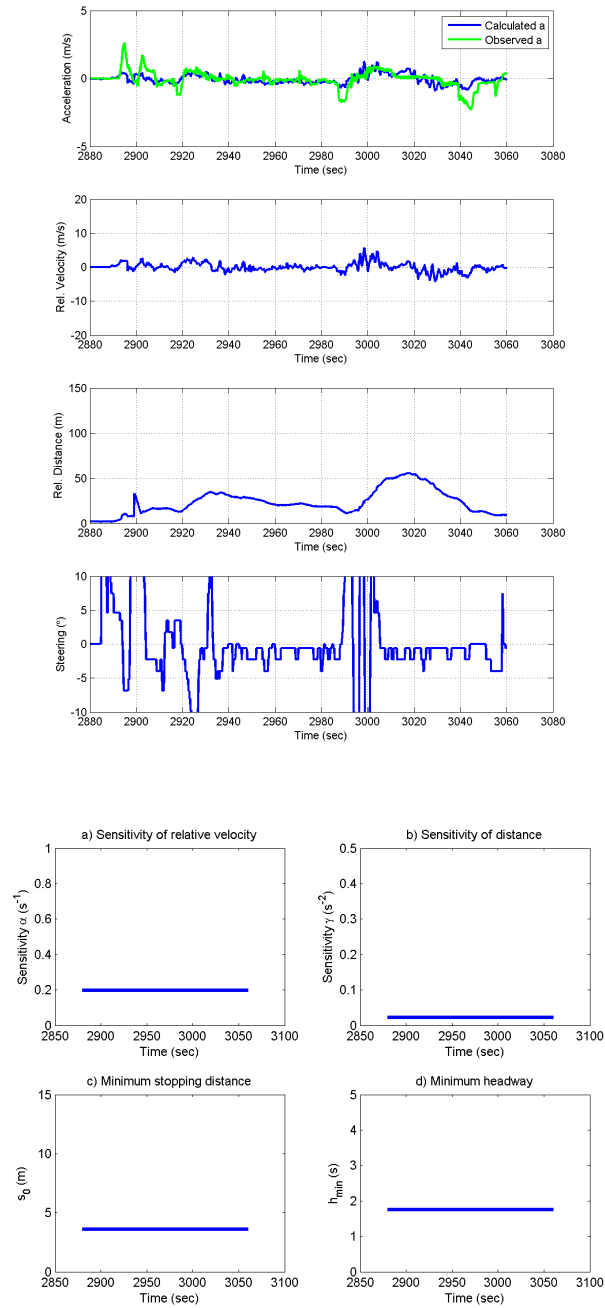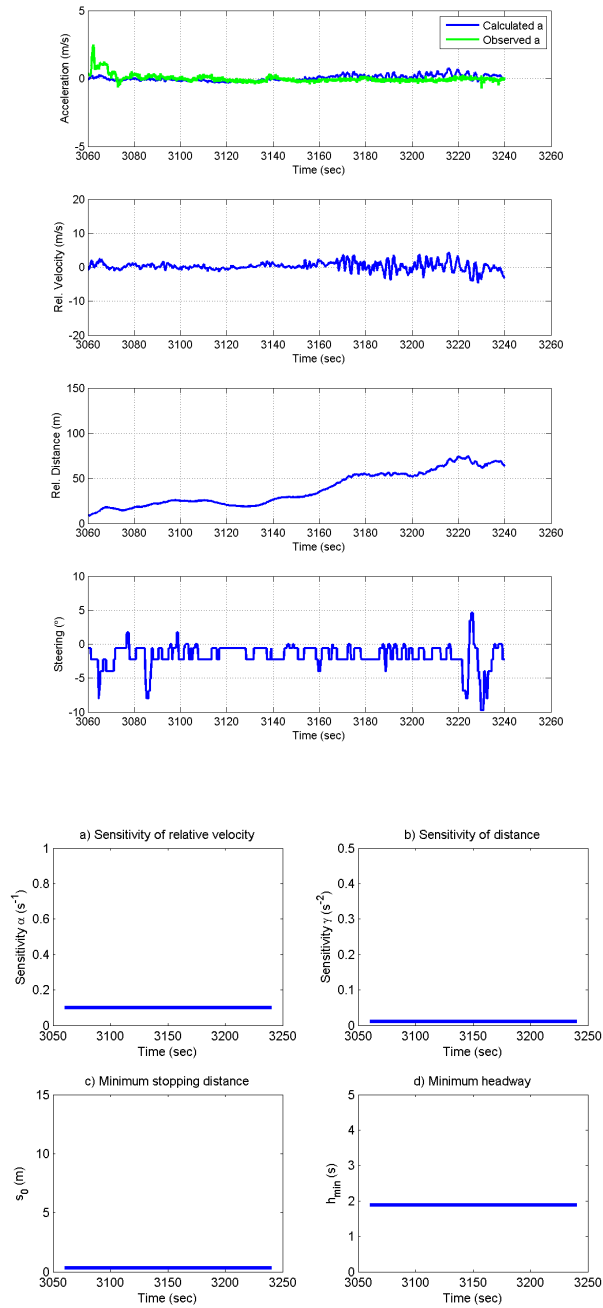| Experiment	Normal driving 24rd October
Number of action points	0 (identified)
All	Car-following, small mismatches due to unexpected braking of car n+1.

Figure B.37: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points, 2880-3060 sec.

Experiment	Normal driving 24rd October
Number of action points	0 (identified)
All	Car-following.

Figure B.38: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points, 3060-3240 sec.

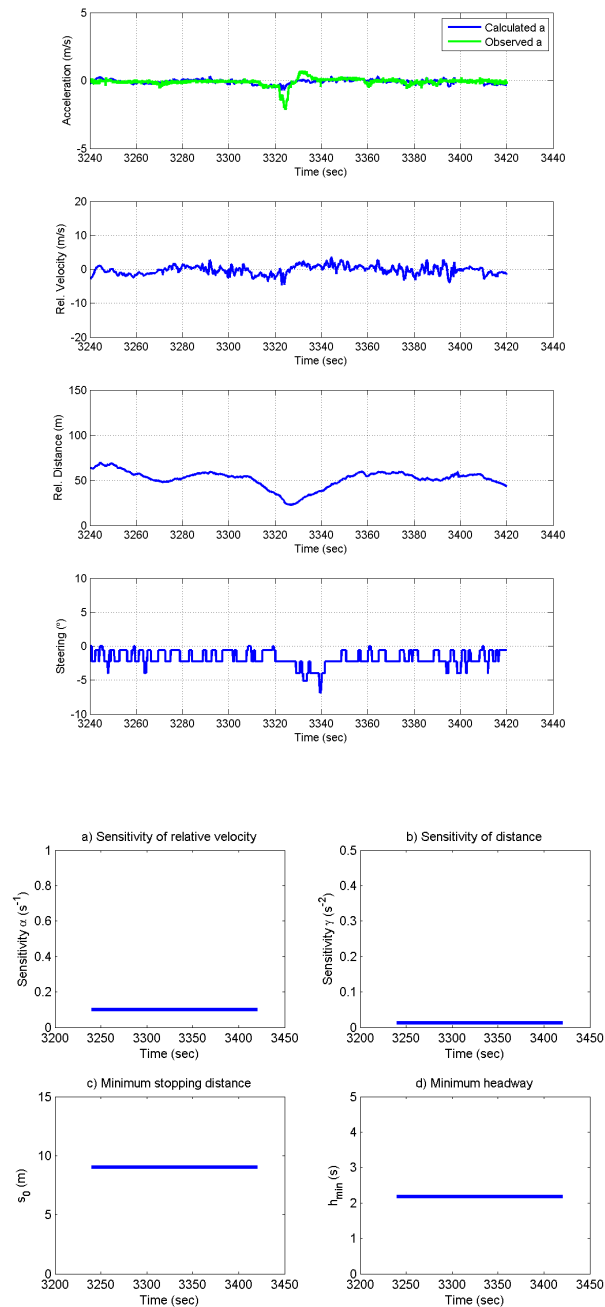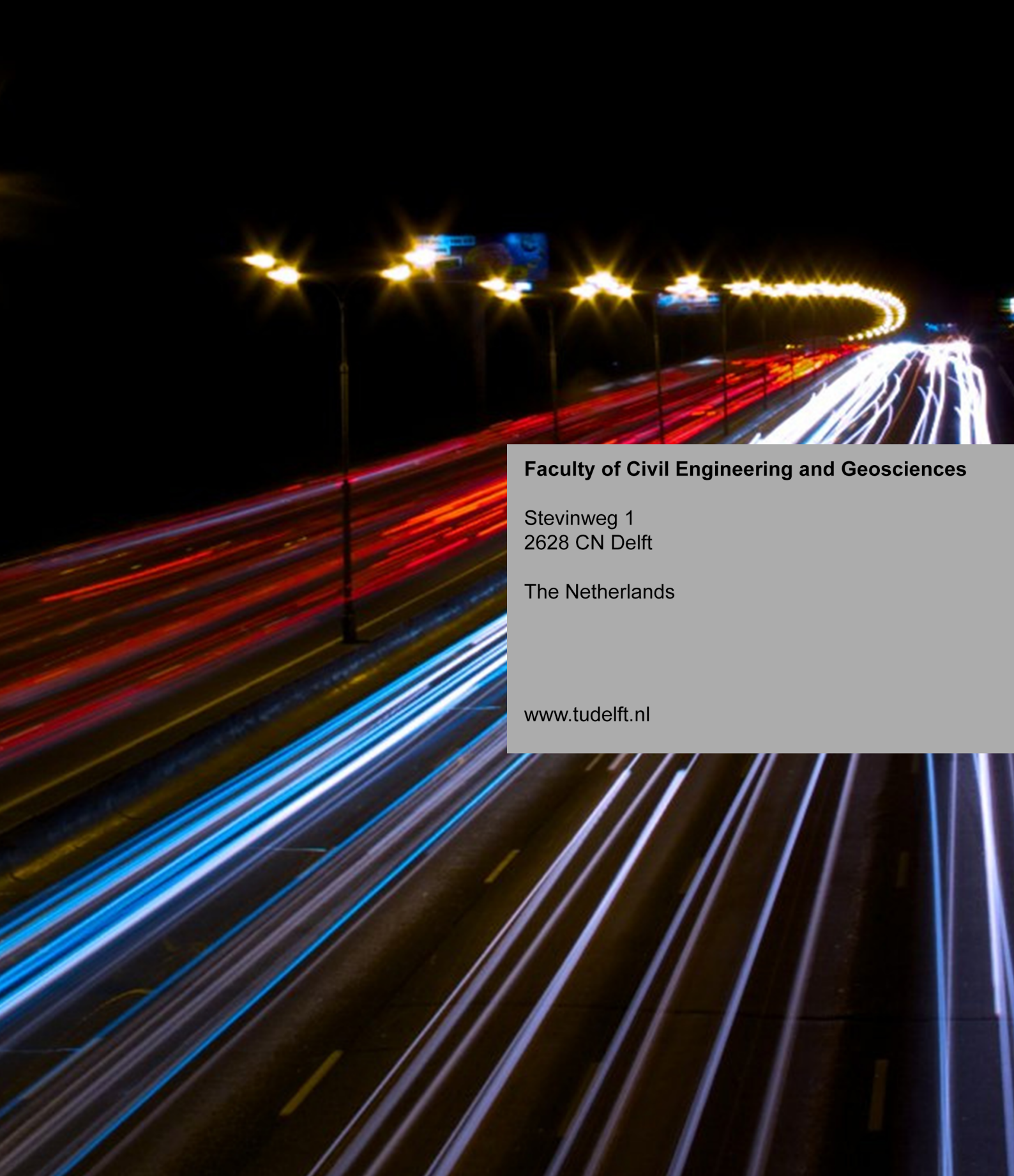| Experiment	Normal driving 24rd October
Number of action points	0 (identified)
All	Car-following.

Figure B.39: Accelerations, relative velocity, relative distance, steering, parameters and estimated action points, 3240-3420 sec.

Faculty of Civil Engineering and Geosciences

Stevinweg 1
2628 CN Delft

The Netherlands

www.tudelft.nl