MEASUREMENT OF HUMAN DRIVER'S AUTHORITY AND IMPLEMENTATION OF ASSISTANCE SYSTEM ON A SIMULATOR STUDY

(AKILLI ARAÇLAR İÇİN SÜRÜCÜ HAKİMİYETİNİN ÖLÇÜLMESİ VE DESTEK KONTROL SİSTEMİNİN SİMÜLATÖR TABANLI UYGULANMASI)

by

PINAR ULUER, B.S.

Thesis

Submitted in Partial Fulfillment

of the Requirements

for the Degree of

MASTER OF SCIENCE

in

COMPUTER ENGINEERING

in the

INSTITUTE OF SCIENCE AND EGINEERING

of

GALATASARAY UNIVERSITY

September 2012

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Date of Submission	: September 25, 2012
Date of Defense Examination	: October 12, 2012

Supervisor	: Assoc. Prof. Dr. Tankut Acarman
Committee Members	: Assist. Prof. Dr. R. Burak Arslan
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Acknowledgements

First, I hold the utmost respect and thanks to Assoc. Prof. Dr. Tankut Acarman for his supervision, support and guidance of this study. I also wish to express my gratitude to him for his criticism and boundless patience in the development of this thesis.

I wish to express my sincere thanks to Assist. Prof. Dr. R. Burak Arslan and Assist. Prof. Dr. Müjde Erol Genevois for their criticisms and contributions to this study.

I thank my friend Can Göçmenoğlu for his great achievement in the simulator development. Without his contributions, it wouldn't be possible to complete this study.

I'd also like to thank my professors and colleagues from the Department of Computer Engineering at Galatasaray University, especially to Serhan Daniş for helping me understand the nature of the things and patiently answering my endless questions.

I owe so much to my professors, colleagues, friends and fellow students at the university for their volunteer participations to the simulated test drives.

Finally, but most importantly, I'd like to thank my family; especially my parents; for their unconditional support, encouragement, patience and boundless love.

Pınar Uluer

25 September 2012

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Abstract

One of the most challenging factors in the development of autonomous vehicles and advanced driver assistance systems is the imitation of an expert driver system which is the observer and interpreter of the technical system in the related driving scenario.

A multi-modal adaptive driver assistance system is presented in this study. The main goal of this visual-based driver assistance system is to determine the human driver's attention and authority level by decoupling the driver's vehicle control in both of the longitudinal and lateral direction in order to trigger timely warnings according to his/her driving intents and driving skills with respect to the possible driving situation and hazard scenarios.

The presented visual-based system consists of three modules; a reference co-pilot driver model, the human driver model and a driver evaluation system. The presented driver assistance system evaluates the driver's driving performance metric computed during the longitudinal and lateral vehicle control tasks as well as the processed information about the surrounding traffic environment consisting of the interactions with the other vehicles and the road situations.

The presented system evaluates the driver's driving skills and attention level by comparing the reference model and human driver's reactions suited in a finite set of decision and maneuvering task. In case of hazard analysis, the system triggers timely warnings pointing the driver's attention at the lateral or longitudinal maneuvering tasks depending on the interpreted situation.

To evaluate the driver's authority, a large set of driving maneuvering tasks are performed. Maneuvers are chosen from cruise control to overtaking scenarios where longitudinal vehicle control or both of longitudinal and lateral vehicle control are persistently required to perform safe driving. The driver is distracted by a cell-phone issued secondary task in order to observe the influence of this secondary task on the reactions of the driver related

to cruise control and the lane keeping maneuvering tasks.

Tests are performed on a vehicle simulator. The collected test-data are pre-processed and the presented metric is calculated for the evaluation of the human driver's driving performance with respect to adaptive cruising and obstacle avoidance maneuvering tasks for a sampled set of 4 drivers with different profiles. In the light of the significant results obtained from the preliminary tests, a second set of simulator tests are performed with 40 test drivers. And a validation model is developed for the reference co-pilot model in order to validate the human driver's maneuvering choices.

Résumé

L'un des facteurs défiants dans le développement des vehicules autonomes et des systèmes avancés d'assistance à la conduite est l'imitation d'un système expert qui est en même temps l'observateur et l'interprèteur du système technique dans le scénario de conduite associé.

Un système multi-modal adaptatif d'assistance à la conduite est présenté. L'objectif principal de ce système qui est basé sur la vision artificielle est de déterminer le niveau d'attention et d'autorité du conducteur humain en découplant son contrôle de véhicule dans le sens longitudinal et latéral afin de déclencher des alertes en temps nécessaire en considérant sa compétence et ses intentions à l'égard de la situation actuelle et des probables scénario de dangers.

Le système qui est basé sur la vision artificielle, est composé de trois modules: un modèle de référence co-pilote, un modèle de conductuer humain et un système d'évaluation de conducteur. Le système de l'aide à la conduite présenté considère à la fois la performance du conducteur humain qui est prélevé pendant la tâche du contrôle longitudinal et lateral du véhicule et l'information traitée à propos de l'environnement routière constitué des interactions avec d'autres véhicules et des conditions de circulation.

Le système présenté évalue les facultés de conduite et le niveau d'attention du conduvteur humain en le comparant au modèle de conducteur référence dans un ensemble fini de décision et les tâches de manoeuvre possible. En cas d'analyse des risques, le système déclenche rapidement des avertissements pointant l'attention du conducteur aux tâches de manoeuvre latérales ou longitudinales en fonction de la situation interprétée.

Nombreuses tâches de manoeuvres de conduite sont effectuées pour évaluer l'autorité du conducteur. Ces manoeuvres sont choisis parmi le scenario de poursuite adaptatif à des scénarios de dépassement où le contrôle longitudinal du véhicule ou le contrôle longitu-

dinal et latéral du véhicule est constamment examiné upour la securite de la conduite. Le conducteur a ete distrait par une tâche secondaire, d'opérer avec un telephone portable, afin d'observer l'influence de cette tâche secondaire sur les réactions du conducteur en considérant les manoevres de conduite adaptatif et la maintien de ligne.

Les tests sont effectués sur un simulateur de véhicule. Les données de test sont pré-traitées et la métrique présentée est calculée afin d'évaluer de la performance du conducteur par rapport aux tâches de poursuite adaptatif et d'éviter l'obstacle pour un ensemble de 4 conducteurs avec des profils différents. A la lumière des résultats significatifs à partir des tests préliminaires, une deuxième série de tests de simulation sont effectués avec 40 conducteurs volontaires. Et un modèle de validation a été développé pour la référence co-pilote afin de valider les choix de manoeuvre du conducteur humain.

Özet

Özerk araçların ve ileri sürücü destek sistemlerinin gelişmesindeki en büyük etkenlerden biri, sürüş senaryolarında teknik sistemin gözlemcisi ve yorumlayıcısı konumunda bulunan uzman sürücü sistemlerinin taklit edilebilmesidir.

Bu çalışmada, sürücüye uyarlanabilir çok modlu bir sürücü destek sistemi sunulmaktadır. Görüntü işlemeye dayalı bu sistemin asıl amacı, sürücünün boylamsal ve yanal araç kontrolünü birbirinden ayırarak, kişinin dikkat ve yetki seviyesini belirlemek, bu sayede, olası sürüş durumları ve tehlike senaryoları bakımından sürücünün niyetine ve sürüş yeteneğine göre doğru zamanda uyarıları tetiklemektir.

Görüntü işleme temelli olan bu sürücü destek sistemi üç modülden oluşmaktadır; bunlar sırasıyla uzman bir sürücü gibi davranan referans sürücü modeli, insan sürücü modeli ve sürücü değerlendirme sistemidir. Sunulan sürücü destek sistemi; diğer araç ve yol durumlarıyla etkileşimleri içeren çevresel trafik ortamının bilgilerini değerlendirir, bu değerlendirme esnasında boylamsal ve yanal araç kontrol görevleri sırasında örneklenen sürüş ölçütlerini de göz önünde bulundurur.

Sunulan sistem, manevra görevleri ve kararlardan oluşan bir sonlu kümeye uygun olarak, referans olarak alınan modelin tepkileriyle sürücünün tepkilerini karşılaştırarak, sürücünün sürüş yeteneklerini ve dikkat seviyesini değerlendirir. Tehlike analizi durumunda sistem, yorumlanan duruma bağlı olarak, yanal ve boylamsal manevra görevlerinde, sürücünün dikkatine yöneltilmiş gerekli ve uygun uyarıları tetikler.

Sürücü hakimiyetinin değerlendirilmesi için geniş kapsamlı bir manevra kümesi seçilmiştir. Bu kümede yer alan manevralar, sürücünün güvenli bir sürüş yaşayabilmesi için sadece doğrusal araç hakimiyeti gerektiren takip göreviyle başlayıp ve de hem doğrusal hem de yanal eksende araç hakimiyeti gerektiren sollama göreviyle son bulmaktadır. Bu görevler esnasında sürücüye cep telefonu kullanmak gibi ikincil bir görev verilmiştir ve bu ikincil

görevin sürücünün araç hakimiyeti üzerindeki etkileri incelenmiştir.

Testler bir benzetim ortamında gerçekleştirilmiştir. Deneyler sırasında toplanan test verileri ön işlemden geçirilmiş ve sunulan performans ölçütü, değişik profillerde 4 sürücüden oluşan bir test kümesi için hesaplanmıştır. Kişilerin doğrusal ve yanal araç kontrolundeki başarıları bu ölçüt göz önünde tutularak değerlendirilmiştir. İlk deneylerden elde edilen sonuçlar ışığında, simulator testleri 40 katılımcıyla daha detaylı haritalar üzerinde tekrarlanmıştır. Ayrıca sürücü destek sistemi için, insan sürücünün davranışlarını denetleyen bir onaylama modeli geliştirilmiştir.

1 INTRODUCTION

1.1 Motivation And Objectives

Driver assistance systems need to have an appropriate understanding of their environment to increase the safety of the drive as well as the safety of the vehicle occupants. To fulfill their function efficiently, these systems have to be designed in order to cooperate with the human driver, i.e. they have to take into consideration the behaviors and intentions of the driver. But this is not easy task because the behavioral characteristics vary from one driver to another. Therefore, it is necessary for the assistance system to consider the driver behaviors in order to infer his/her intentions and to achieve a human-like understanding of the current traffic situation to warn the human driver.

With the development of the in-vehicle device technology with all the stand-alone electronic components, adjusting the driver assistance system's warnings considering the human driver's driving characteristic and skill is feasible. Otherwise an assistant system may overload the driver and cause distraction.

A promising way to overcome this problem is to monitor the human driver's authority on the vehicle control and to detect when he/she doesn't perform the driving task according to his/her driving characteristics and skill.

The objective of this thesis is to monitor the human driver's driving performance and to infer the evolution of his/her authority level on the vehicle control in both longitudinal and lateral direction by observing his/her driving intents and skill, in order to adjust the driver assistant system for triggering the necessary warnings when it is meaningful and worthy.

1.2 Vision Zero Initiative

In 1997, the Swedish Parliament introduced a new and highly challenging approach to road traffic safety. The "Vision Zero" is built around the ethical basis that: "*It can never be ethically acceptable that people are killed or seriously injured when moving within the road system*" (Tingvall and Haworth, 1999).

The safety paradigm is based on the idea that fatalities and severe injuries in road accidents can be avoided even if all the accidents can't be avoided, and it can be summarized as "*No loss of life is acceptable*".

The traditional transportation systems are not adequate to achieve this goal, because the main focus points of a traditional transport system design are usually the maximum capacity and the mobility but not the safety. The road-user approach to traffic safety is based on this principle, and the human traffic participants are held responsible for their own safety as well as the other participants' safety. Therefore the countermeasures focus only in changing the human driver's behavior.

Vision Zero Initiative opposes the road-user approach that the road user is the only responsible of the traffic accidents. It divides the responsibility between the road users and the system designers. The system designers are held responsible for the design as well as the safety level within the entire road transportation system and they have to take the necessary measures in case of human fallibility. The road users' responsibility consists of the following of the traffic rules set by the designers and they are prone to make mistakes (Whitelegg and Haq, 2006).

Both of the two approaches have their own benefits and draw-backs, (Larsson et al., 2010). Although the Vision Zero approach doesn't so far represent a success story according the general statistics presented in the study of Rosencrantz et al. (2007), inspired by the studies of Brude (2005) and Vagwerket (2006), but it is promising considering the steady decrease in the annual number of casualties and serious injuries in traffic accidents in Sweden. And it is worth to notice that the number of countries which adopt the Vision

Zero approach and try to adapt their transportation system is increasing. The approach is popular in Norway,(Elvebakk and Steiro, 2009), in the United Kingdom,(Whitelegg and Haq, 2006) as well as in China,(Ding, 2010) and in many states of USA such as New York and Oregon.

1.3 Technological Trends

With the guidance of the Vision Zero approach and the development of the in-vehicle technologies and stand-alone electric devices, the idea of reducing the number of traffic accidents which are one of the major causes of human death seems more possible.

The evolution and development on the automotive industry have a great contribution in the reduced number of traffic fatalities since the 90's with the vehicles equipped with advanced driver assistance systems which controls and supports the human driver in command.

These systems offers assistance to the human driver in the tasks of, (sta, 2008):

- Cruise (Adaptive cruise control system)
- Collision avoidance (Pre-crash system)
- Lane departure (Lane departure warning system)
- Lane change (Lane change assistant)
- Blind spot detection
- Automatic parking
- Traffic sign recognition
- Navigation (In-vehicle Navigation System)
- Awareness (Driver drowsiness detection and Vehicular communication systems)

A list of car manufacturers whose vehicles are equipped with these systems can be found in the study of Shaout et al. (2011).

1.4 Literature Study

One of the major causes of the traffic accidents is the human failure, the drivers not paying attention due to several reasons. Finding the ways of reducing human induced error is a popular topic in the intelligent transportation systems research.

With the contribution of the ongoing academic and industrial studies, the zero accident vision may become an absolute reality.

Since the majority of road accidents are due to driver-related errors, it is important to design and develop safety systems which will provide the necessary support to the human driver in order to assist him/her along his/her driving task. To minimize human driver errors, the assistant safety systems should monitor the driver's control authority and driving behavior. Therefore the integration of the human driving behavior models into the design and development of the assistant systems plays an important role on the driving safety enhancement.

Modeling the human driver behavior is a popular research field in the intelligent transportation system studies. Driver models have taken great amount of attention in the last 50 years.

The first studies on driver modeling focused mainly on the task of cruising in the 1950's. A comprehensive review of the historical development of car-following models is available in the literature, (Brackstone and McDonald, 1999).

According to Brackstone and McDonald (1999), the most well-known longitudinal human driver model is the Gazis-Herman-Rothery (GHR) model which dates from the late fifties, (Gazis et al., 1961). The formulation is based on the acceleration of the preceding vehicle and the relation is derived from the proportion of the relative velocity to the relative distance between the leading and preceding vehicles sampled at an earlier time determined by the reaction time of the human driver. There are several studies on this model which focuses on the optimization of the GHR equation parameters where the most reliable estimates are obtained by Chandler et al. (1958), Herman and Potts (1959), Hoefs (1972), Treiterer and Myers (1974) and Ozaki (1974).

According to Gipps, the early longitudinal control models present a mathematical robustness but the parameter selection isn't accurate to identify the relationship between the driver behavior and vehicle traits. In his study, Gipps propose that each driver specifies the limits of his/her desired braking and acceleration rates which constitutes his/her response reaction to the leading vehicle, (Gipps, 1981). Gipps defends that the model parameters are not the same for all of the drivers and their selection emphasizes the individual differences on the desired following distance and velocity.

In their study, Bareket et al. propose a modified version of the Gipps model and they test the model with naturalistic driving data, (Bareket et al., 2003). The study shows that when the model is supplied with the realistic driving data, it is able to reproduce the characteristic of the real traffic flow.

Apart from the adaptive cruising models, there are also ongoing studies on the human driver lateral vehicle control mainly focused on the lane change behavior of the driver. There exists various studies on the literature which models the different aspects of the lane changing behavior using several methods. The studies' main focus is to analyze and model the human driver lane-change behavior in order to predict possible lane-change maneuvers or to infer the lane-change intent of the driver using the human driver performance metrics.

Gipps (1986), Ahmed (1999) and Kesting et al. (2007) use hierarchical decision method and longitudinal dynamic model for modeling the lane change decision behavior where Oliver use Hidden Markov Models to recognize lane change state. Mandalia and Salvucci (2005) uses Support Vector Machines in their study, while in another study Salvucci et al. (2007) use a computational model to perform the same task of recognition. In the other hand, McCall et al. (2007) uses Sparse Bayesian learning to infer lane change intent of the human driver. A review of these models can be seen in the work of Xu et al. (2012).

The use of the human factors metric is important for the studies on the human driver behavior evaluation. One of these studies is the European RoadSense project, Chin and Nathan (2004). The project aims to implement an evaluation methodology for the human driver based on his/her driver behavioral indicators. These behavioral indicators consist of several metrics representing the lateral control, visual management, speed adaptation, interactions with the surrounding vehicles and situation awareness. A detailed list of the behavioral metrics can be found in the study of Bezet et al. (2006).

The behavioral metrics play an important part on the evaluation and interpretation of the human driver's driving characteristics and choices. With the development of the in-vehicle technologies, it is possible to monitor the driver but these systems may also increase the potential of the in-vehicle distraction. This problem represents one of the most challenging constraints in the design of the assistance systems which should warn the driver accurately not causing any distraction issued by the overloading warnings. Therefore it is crucial for the assistant system to achieve an understanding of the driver behaviors to warn him/her when it is necessary.

The recent studies shows that modeling human driving behavior involving cognitive part may be considered as a contribution to active safety of the land vehicles.

Cognitive models can be used to model the human driver behavior, to estimate the mental workload in case of external or internal disturbances and to determine driving-related human factors. The studies on the computational cognitive models are important for the assistant system to achieve a human-like situational understanding about possible hazard situations on the road.

The cognitive approach may be used by the driver assistance systems to evaluate the multi-modal driver in-the-loop in terms of his/her intents versus the sensed scenarios, and trigger timely warnings, interventions by considering the driver's authority. The assistance systems, which evaluate the human driver by comparing his/her reactions and intents to the reference driver's decisions, require a human-like understanding of the human driver's actions to generate timely warnings or interventions to avoid possible accidents with real-time feed-backs.

One of the systems that assess the driver's operating characteristics and modify the vehicle control for improving the drive safety on a real time basis, is the Control Authority Transition (CAT) System presented in (Acarman et al., 2003). The CAT system emulates a reference driver to evaluate the situations and possible dangers represented in accordance with the driving task, the driving conditions and the state of the driver.

The recent studies show that the cognitive modeling of the human behavior can be applied to the driving scenarios.

In their study, Bellet and Tattegrain-Veste (1999), presents a cognitive framework to represent the human driver's driving knowledge. COSMODRIVE (Cognitive Simulation Model of the Driver) is a model which is constructed by different modules, each corresponding to a driving task related cognitive activity.

Thierry Bellet (2009) carries their research to model the mental representations of car drivers by following the tradition of Human Information Processing theories. They model the situation awareness of the human driver by using the driver's mental representations and define the awareness level of the human driver. Based on the significant results obtained by the use of their method they propose to use driving schema formalism to combine the operative and procedural knowledge in order to achieve an understanding on his/her level of control.

In another attempt to conceive a human driver behavior model, Song et al. (2000) also use a cognitive approach to form a driving knowledge database and to model the cognitive process of driving activity. They use the cognitive approach with a simulated driver and they manage to constitute a set of possible behaviors where the simulated driver choose to perform one behavior from this set.

In another study, Wu and Liu (2006) propose a computational architecture which integrates the queuing network approach and the symbolic approaches of the model human processor. The QN-MHP (Queuing Network-Model Human Processor) is a cognitive model which represents the human driver information processing as a queuing network also considering the neuroscientific and psychological findings. The proposed model consists of the three subnetworks to represent perception, cognition and motor functions of the human driver. This cognitive architecture is also used in other studies in order to model the human driver's car following behavior and vehicle control according to the velocity and steering wheel angle parameters, (Wu and Liu, 2006), (Wu and Liu, 2007).

Ciardelli et al. (2011) also presents a cognitive approach for modeling the interactions and detecting the dangerous situations among the human driver, the intelligent vehicle and the surrounding ones. The proposed model is used in order to define a set of events to assess the driver control and to manage potentially dangerous inter-vehicular situations.

In the other hand, fuzzy systems are also used to approximate human reasoning to handle the uncertain data related to driving scenarios. A fuzzy controller is implemented to regulate the vehicle actuators, (Milanes et al., 2011) and a fuzzy rule base is used to actuate maneuvering tasks such as braking and driving slowly, (Hulnhagen et al., 2010).

Another of the popular methods is the probabilistic inference models. They are also used in order to model the uncertain behavior of the human driver. The probabilistic inference methods, mostly Bayesian Networks, are studied by the researchers working on the autonomous vehicle or driver assistance system domain.

In their work, Gindele et al. (2010) used Dynamic Bayesian Network to model a filter to estimate the current state of the autonomous vehicle and the surrounding vehicles in order to perform the necessary decision making and motion planning by achieving a situational understanding of the current traffic scenario.Dagli et al. (2003) also used Bayesian Networks in their work to model driver behavior and to recognize the action taken by the driver.

Another approach to characterize the driver behavior is to use pattern recognition methods. Zhang et al. (2010) propose to extract the relevant patterns to the driver's skill level by measurement of driver's behavior and the vehicle response. They use the DFT coefficients of the steering handling dynamics to recognize the difference between the expert and low level skilled drivers.

The effects of the secondary task on the human driver's performance is also a popular research study. In their research, Ersal et al. (2010) emphasize that secondary tasks may have individual effects on each driver, they propose to use a modeling framework based on neural networks to characterize the normal driving behavior of a driver performing the main driving task without any secondary task. They compare the model predicted behavior with the actual behavior of the driver to observe how each individual is distracted by the secondary task by using a trained support vector machine.

1.5 Thesis Outline

In the first chapter of this thesis, the motivation and objectives of the thesis are presented with the technological trends and concepts alongside the background information on the evolution of human driver modeling methodologies.

The remainder of this thesis is organized as in four chapters.

The visual-based driver assistance system is presented in Chapter 2. The general architecture of the system and its modules are detailed and the vehicle simulator used for the evaluation of the human driver's authority level is introduced in this chapter. The reasons behind the choice of a vehicle simulator to run the tests are discussed alongside the vehicle simulator setup.

The vehicle simulator study with two-phased test runs is presented in Chapter 3. In the first part, the preliminary results of the presented evaluation system for a sampled set of drivers are detailed and discussed. The second and third parts consists of the simulator tests with forty participants, the driving tasks and maps are detailed and the relevant results are presented.

The development of reference co-pilot validation model for two type of maneuvering, braking and lane changing maneuvers, is described and the validation results are presented in Chapter 4.

And finally, conclusions and directions for further research are discussed in Chapter 5.

2 VISUAL-BASED DRIVER ASSISTANCE SYSTEM

A vision-based active safety system is presented to prevent possible traffic accidents during lane change maneuvering and lane following tasks. The active system considers that the driver is always in-the-loop and in case of lane departure detection or lane change unintentionally into the path of the coming vehicle, visual and audio signal is generated to warn the driver. The vision-based system, which was presented in the study of Yuksel and Acarman (2011), consists of the sensor suite of one camera looking forward to percept lane borders and detect possible lane departure in a sensing range of 60 meters, two web cameras placed into the side mirrors detecting the oncoming vehicles in the adjacent lanes in a sensing range of 24 meters. Vision-based system senses the surrounding vehicles. For redundancy, relative distance with the leading vehicle is measured by a LIDAR of 80 meters sensing range. The functionalities of the setup are elaborated in the study of Cayir and Acarman (2009). The sensor coverage areas are illustrated in Figure 2.1.

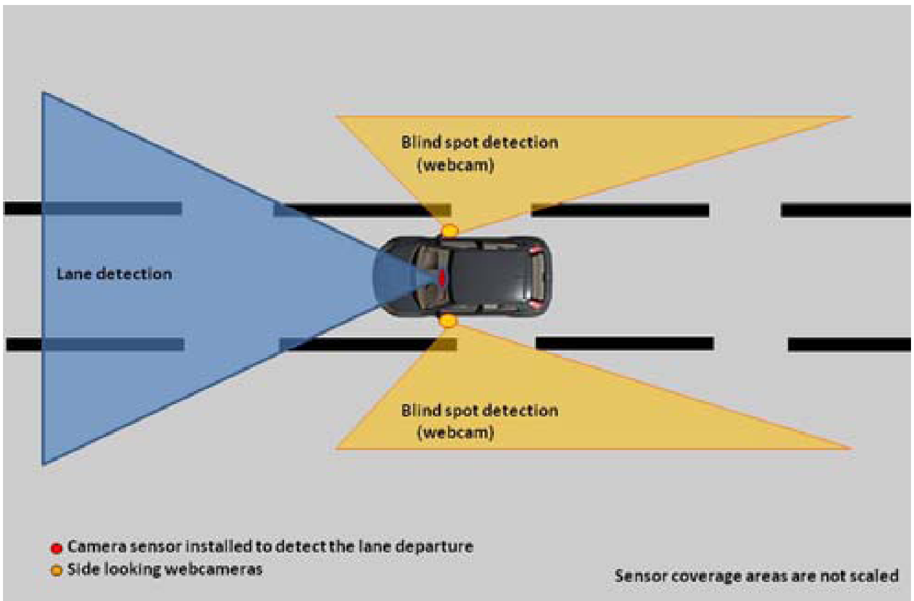

Figure 2.1: Sensor Coverage Area, (Cayir and Acarman, 2009)

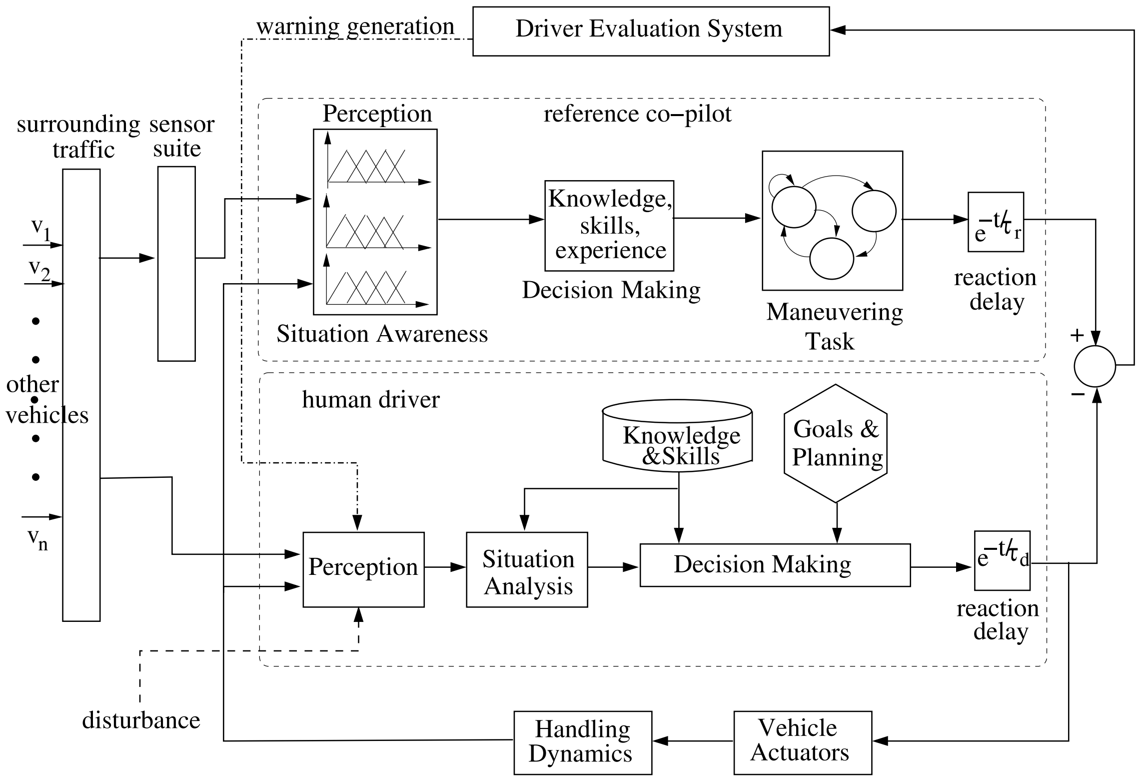

Figure 2.2: The General Architecture of Human Driver Model and Reference Co-Pilot Model

2.1 Driver Assistance System

The general architecture of the presented reference co-pilot model and the human driver model are shown in Fig. 2.2.

The sensor suite module collects the sensor outputs and delivers the relevant information to the human driver and reference co-pilot models. The sensor suite processes the data coming from the surrounding traffic environment and the vehicle ego motion about its local axis.

The surrounding traffic module represents the environment which surrounds the vehicle. It consists of the traffic and road environment. It takes into consideration not only the traffic and road properties such as traffic flow or specific limitations on the current road but also the interactions among the vehicles and their relative positions. The vision-based system, which was presented in the work of Yuksel and Acarman (2011), senses the

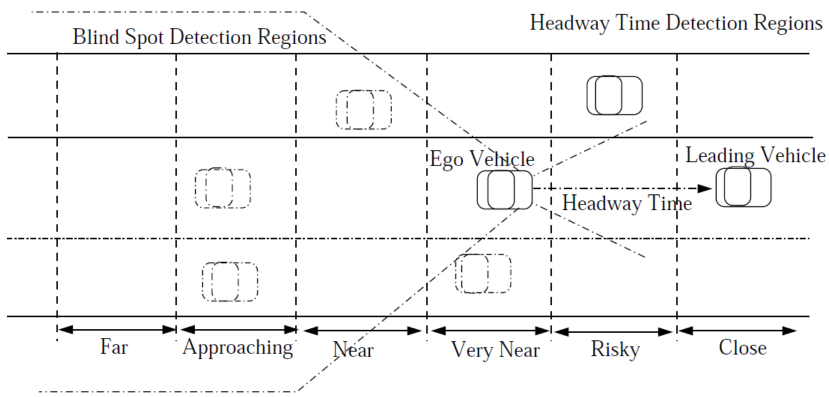

Figure 2.3: Surrounding vehicles are sensed by the web cameras, front looking camera and LIDAR, (Yuksel and Acarman, 2011)

surrounding vehicles (leading vehicle and the oncoming vehicles from the adjacent lanes) and detects possible lane departure scenarios, as seen in Figure. 2.4.

The vehicle handling dynamics module is significant in terms of feed-back for the monitoring task because it may reflect the human driver's driving ability and his/her authority and experience on the vehicle control expressed by the use of the actuators.

The vehicle actuators module represents the vehicle actuators such as acceleration and brake pedals, steering wheel and left/right lane change indicators. The human driver regulates the actuators to achieve the maneuvering task.

2.1.1 Human Driver Model

The presented human driver model is based on the general structure of the COSMODRIVE and the schematic description of the situation awareness process of Endsley, (Endsley, 1995).

The perception module of the human driver model represents the driver's perception of the vehicle environment. The data coming from the sensors and surrounding traffic elements are perceived by the human driver. The perception can be subject to disturbances. The perception of the current situation elements constitutes the first level of the driver's situation awareness process.

The situation analysis module is important at the stage of understanding the current situation which is based on perceived elements and during the task of decision making by using the gathered data. The comprehension of the current situation elements is the second level of the situation awareness process.

The decision making module takes into consideration the driver's objectives and provides a strategy to achieve these objectives by interpreting the perceived data and conceived information. This strategy is evaluated according to the facts and is taken into consideration in the decision making phase along with the driver's past knowledge of the similar scenarios and his/her skills. The reaction delay module represents the lag of the driver's muscular (arm/foot) response once the decision is made. The perception and situation analysis phase, and then the decision making task is finalized in an action response which is expressed by the use of the actuators. This module simulates the reaction delay issued from the cognition phase. The reaction delay is considered and computed according to the driver characteristics. The fact that the driver is mentally occupied or is an elderly/ teenage driver makes difference in the variable, denoted by τ_d, which represents the reaction delay as denoted in Fig. 2.2.

2.1.2 Reference Co-Pilot Model

The evaluation of the human driver is done by the reference co-pilot block. The block consists of four connected modules similar to the human driver block, involving transfer functions on situation awareness, decision making, maneuvering task and reaction. The data collected from the sensors is processed to model the situation awareness of the driver by using fuzzy sets which represent the reference driver's perception in the surrounding traffic

The situation awareness module processes the sensor data coming from the CAN-Bus of the vehicle, or from the simulation parameters. The data collected from the sensors is processed in order to model the situation awareness of the driver by using fuzzy sets. Each fuzzy set simply represents the expert driver's perception in surrounding traffic considering both of the longitudinal and lateral directions.

Fuzzy logic provides a simple and flexible approach to handle uncertain data and gives the opportunity to approximate human reasoning by the use of the membership functions which replace the thresholds of binary logic.

In the presented expert system, 3 input variables are used to represent the human driver's perception in both of the longitudinal and lateral direction. The membership functions of the fuzzy input variables are defined subject to the sensor coverage areas, (interested readers may refer to the study of Cayir and Acarman (2009) for details on the selection of the camera sensors).

The first fuzzy input variable is the headway time between the ego vehicle and the leading vehicle. The headway time is used to evaluate the longitudinal control of the human driver model. The label 'risky tracking' indicates that the ego vehicle is really close to the leading vehicle and there is a high risk of collision whereas the 'close tracking' indicates that the headway distance is not safe enough to brake gradually. The 'safe tracking' label indicates that the ego vehicle is at a safe distance from the leading vehicle and the 'free flow' label indicates that there is no vehicle in front of the ego vehicle.

The second and third fuzzy inputs are blind-spot values and the estimated distance to a possible lane crossing, respectively. These inputs are used for the evaluation of lateral control of the human driver.

The blind-spot values represent the oncoming vehicles on the left and right adjacent lanes. The detection system is adjusted on the basis of the perception-reaction time of the driver. The blind-spot values are detected for each side of the vehicle. The blind-spot values assess the distance of the oncoming vehicle and denote the relative zones as 'empty', 'far', 'approaching', 'near' and 'very near'. The notation is motivated by the sensing range of the web-cams mounted on the side mirrors.

The estimated time for possible lane departure of the subject vehicle is measured in function of its lateral displacement. This distance is derived from the equations of the yaw angle and the lateral displacement of the vehicle, Acarman et al. (2003). The 'left' and 'right' labels indicate that the vehicle is closer to the left or right lane but won't cross the lane boundaries whereas the 'left departure' and 'right departure' labels indicate that the vehicle will cross the lane boundaries. The membership functions for the input variables are denoted in Figure 2.4.

The situation awareness module produces 4-tuples representing the situation of the vehicle in the traffic. These 4-tuples are coupled by the drivers characteristics in the decision

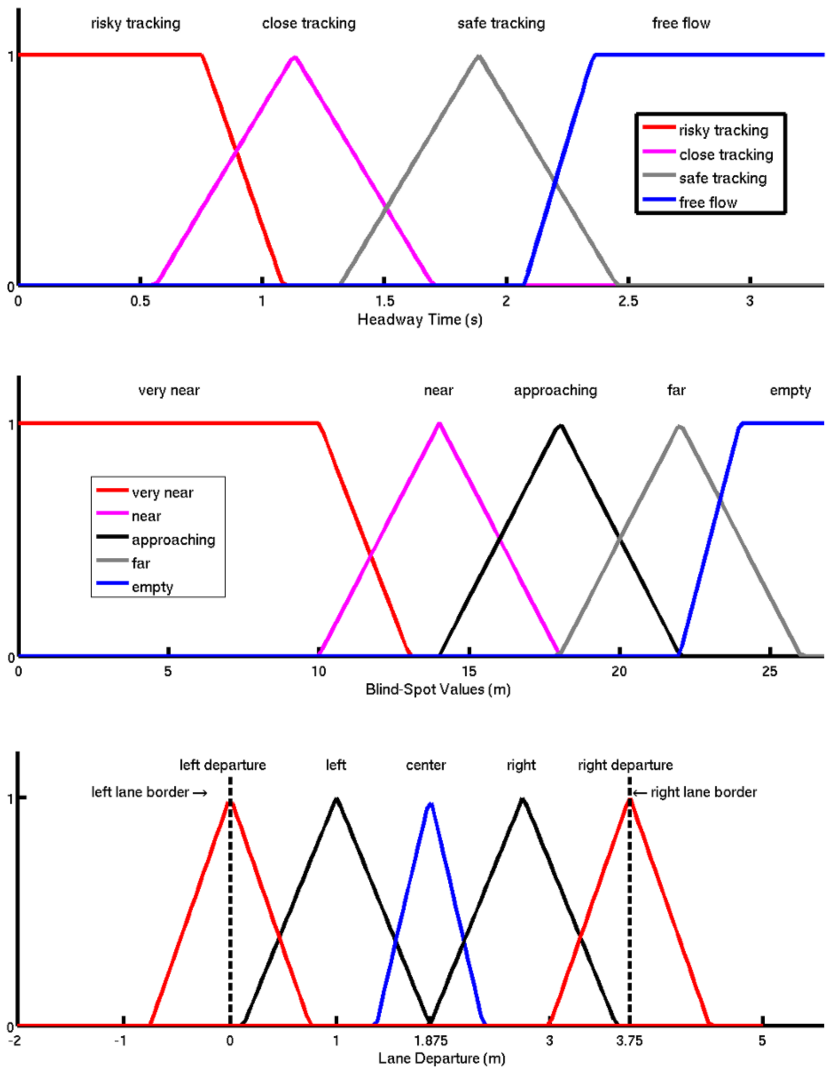

Figure 2.4: Membership Functions of Situation Variables

making module. The 4-tuple is composed by the headway time (*ht*), left (*lbsv*) and right (*rbsv*) blind-spot values and lane departure (*ld*) labels as given in:

$$\Omega = \{ht, lbsv, rbsv, ld\}$$

Then the resulted data is processed according to the human driver's driving knowledge and skills in the decision making module. Finally a finite state machine constructed by a finite set of maneuvering tasks is used to compare the expert driver and the human driver's reactions to evaluate the driver's decision and reaction delay.

The functioning of the decision making module of the reference driver model is based on the prediction of the human driver cognitive activities according to his/her knowledge and skills. The driver's knowledge is not limited only by his driving knowledge obtained by the past driving scenarios; it also covers the traffic regulations and environment. And his/her driving skills are the proof of his/her experience (experienced or novice) on the driving task. Each individual has different driving skill levels, driving habits and capabilities, therefore this module should be modified according to the driver. These modifications are taken into consideration in the specifications of transition properties of the behavioral set in the maneuvering task module.

The reference co-pilot's behavior set is a restricted set constituted by six behavioral nodes. The nodes and the transition conditions among them are modeled as seen as in Fig. 2.5.

This model is used in order to estimate the driver's expected response to the possible driving scenarios which occur in freeway traffic. These nodes are “Following" (Follow), “Lane Keeping Maneuvering" (LKM), “Braking Maneuvering" (BM), “Braking and Lane Keeping Maneuvering" (BM&LKM), “Right Lane Change Maneuvering" (RLC), and “Left Lane Change Maneuvering" (LLC).

The transition conditions are determined based on the headway time with the leading vehicle, oncoming vehicle in the adjacent lanes and the lane departure of the subject vehicle. The conditions which satisfy the switching among the behavioral nodes are listed below:

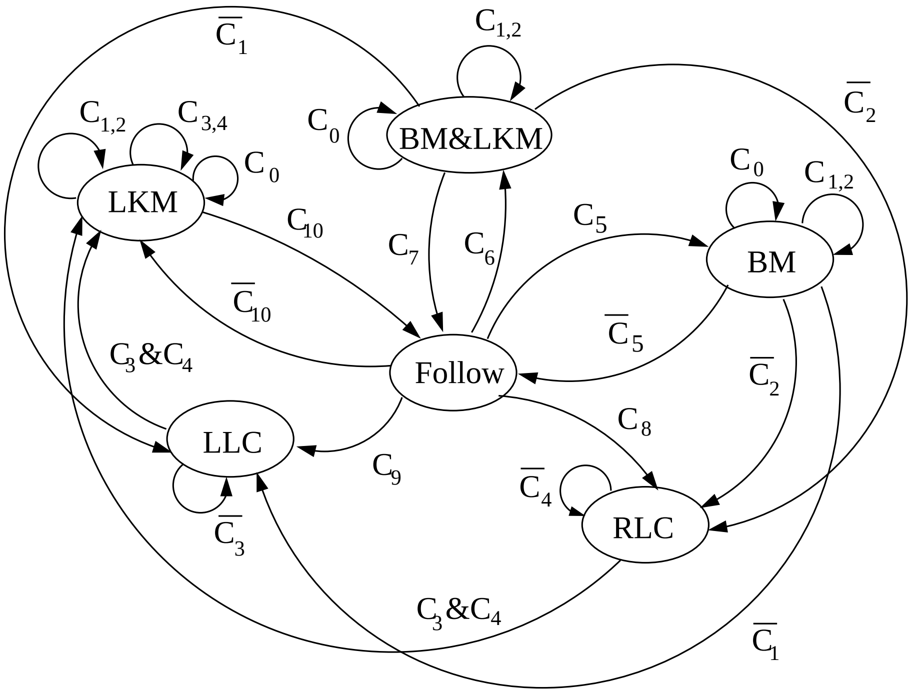

Figure 2.5: Finite State Machine Representation of Maneuvering Sets

C_0: The probability of the existence of surrounding vehicles.

$C_{1,2}$: The occupancy probability of the oncoming vehicle on the adjacent lanes, respectively left and right.

$C_{3,4}$: The probabilities on left and right lane departure.

C_5: The probability of front collision calculated by the headway time.

C_6: The probability for switching between “FOLLOW" and “BM&LKM" is expressed in function of C_3, C_4 and C_5: $C_6 = C_5 . (C_3 \,||\, C_4)$

C_7: The probability for switching between “BM&LKM" and “FOLLOW" is expressed in function of C_3, C_4 and C_5: $C_7 = C_5' . (C_3' \,||\, C_4')$

$C_{8,9}$: The probability of transition between “FOLLOW" and “LCM" respectively right and left lane. It is expressed in function of C_2, C_3, C_5 and RLI or LLI (right and left lane change indicator): $C_8 = (C_5 \,||\, RLI)$ & C_3 & C_2

C_{10}: The probability of transition between "FOLLOW" and "LKM" is expressed in function of lane departure warnings C_3 and C_4: C_{10} = (C_3 || C_4)

The finite state machine, which consists of the presented maneuvering tasks, is used in order to evaluate the driver's maneuvers by decoupling the longitudinal and lateral control of the vehicle. The resulting maneuvers are compared with the human driver's maneuvers to check the driver's decision and reaction timing.

The reaction delay module of the reference co-pilot driver model is similar with reaction delay module of the human driver model and it is adjusted according to the fact that the driver responds accurately following his/her decisions, though the reaction delay of the reference co-pilot, τ_{ref}, is set to 0.7 seconds, which is a given parameter for an attentive driver, Acarman et al. (2003).

2.1.3 Driver Evaluation System

The driver evaluation system compares the human driver's reactions with the reference co-pilot system's reactions based on a finite set of decisions and maneuvering choices. The performance metric is defined by $J_{total} = J_{long} + J_{lat}$ where

$$J_{long} = k_1 \frac{1}{ht} + k_2 |a| \tag{2.1}$$

$$J_{lat} = k_3 |r| + k_4 e^{-\left(\frac{1}{|y-1.875|}\right)} \sigma \tag{2.2}$$

The longitudinal vehicle control performance metric (J_{long}) is calculated in terms of headway time (*ht*) and acceleration (a) whereas the lateral vehicle control performance metric (J_{lat}) is calculated in terms of yaw rate (r) and lateral displacement of the vehicle with respect to lane borders (y) and the surrounding vehicle on the adjacent lane (σ), where the lane center is situated at 1.875 meters. The positive coefficients, denoted by k_i for i=1,2,3,4 are used for the calculation of the performance metric.

In case of the presence of a leading vehicle, the metric increases when the driver approaches to the leading vehicle. The fact that the driver cannot adjust the yaw rate or the acceleration of the vehicle according to current driving situation also causes the metric to increase. Another factor which increases the performance metric is the lane keeping ability; if the driver cannot maintain the vehicle in the center of the lane and there is a possibility of lane departure then he/she is penalized if there are oncoming vehicles from the adjacent lane. The penalization is done according to the distance sensed from the blind-spot camera. If the oncoming vehicle is labeled as 'very near', then the term σ in (2.2) is replaced with 4 and it decreases if the relative distance increases or the vehicle is out of sight.

The metric is formulated accurately to emphasis the changes in the human driver's performance which may cause hazardous traffic situation. The slope of (2.1), (2.2) increases when the driver performs poorly in terms of inadequate reaction to fulfill safety requirements.

2.2 Vehicle Simulator Developed for Test Drives

A simulator platform is chosen to perform the driving tests. The reasons for the use of a vehicle simulator are:

- the possibility to create the same traffic conditions with different test drivers, and the repeatability of the test drives,
- the repeatability of the tests in case of accidents,
- the cost effectiveness.

2.2.1 CanSim

The CanSim Vehicle Simulator used for the test drives, is created by Can Göçmenoğlu for his terminal project to obtain the degree of Bachelor of Science.

The simulator is developed in C programming language and uses OpenGL graphics. It offers an accurate driving experience with the depth in the perception of the graphics and the random city noise.

The map editor of the simulator allows creating different maps for different traffic scenarios with the various blocks from the object library. The library consists of the basic elements of the traffic and road environment. The object blocks which represent these elements are:

- 2-3-4 or 6-lane freeways,
- cross sections,
- road curvatures,
- traveling vehicles,
- speed limitation signs,
- traffic lights with their timings,
- stationary or traveling vehicles with a constant velocity,
- stationary obstacles,
- buildings of various heights
- pavement stones.

A screen-shot of the vehicle simulator can be seen in the following chapter in Figure 3.9. Left and right mirrors displaying the oncoming vehicles from the adjacent lanes, and rear mirror displaying the rear traffic is included to create full information about the surrounding traffic to the simulator driver.

The vehicle simulator is also equipped with a driver assistance system which triggers various warnings according to the current traffic situation. The system monitors headway distance, detects lane departure and blind-spots to determine the distance of oncoming vehicles from adjacent lanes.

The simulator triggers audiovisual warnings when the driver neglects to keep a safe headway distance, approaches or crosses the lane boundaries and initiates a lane change maneuver when there are oncoming vehicles on the intended lane. The simulator offers also an overtaking assistant which warns the driver when he/she initiates an overtaking maneuver in the case of an oncoming vehicle in a previously specified distance. The overtaking assistant also indicates if the lane is available when the driver turns on the lane change indicator.

2.2.2 Data Collection

The vehicle simulator records all the data concerning to the human driver's driving characteristics and the surrounding traffic elements.

The simulator collects the relevant data and delivers the time-stamped data to MATLAB via an UDP connection to be pre-processed. The system works off-line for now because of the time constraint issued by the MATLAB software.

The test drive data collected from the vehicle simulator consist of:

- two-dimensional position information,
- velocity,
- acceleration,
- yaw rate,
- steering wheel angle,
- lane change indicators,
- throttle and brake pedal pressures,
- left and right blind-spot values,
- distance from the center of lane,

- lane departure alerts,
- headway time alerts,
- overtaking assistant alerts

for the human driven vehicle model.

In the presence of the other vehicles, which are traveling along the road with a constant velocity, the simulator also collected the data relevant to the 10 closest surrounding vehicles:

- Two-dimensional position information,
- relative distance with the subject vehicle,
- identification number

data of the 10 vehicles are obtained from the vehicle simulator.

A binary variable which represents the change of the traffic lights is also included in the data collection.

2.2.3 Simulator Setup Components

The simulator setup consists of:

- a white-screen,
- a projector,
- 2 stereo speakers,
- a Logitech Driving Force GT steering wheel with connected throttle/brake pedals (see Figure 2.6.)
- a web-cam,

Figure 2.6: Logitech Driving Force GT Steering Wheel and Throttle/Brake Pedals

- a main computer for the test operator to run the simulator.

The driving scene was projected on a white screen located 1 meter in front of the test participant and it was displayed at 1024 x 768 resolution. The test drives consisting of different maps were initiated consequently by a human operator situated out of the visual field of the test driver. The setup can be seen in Figure 2.7.

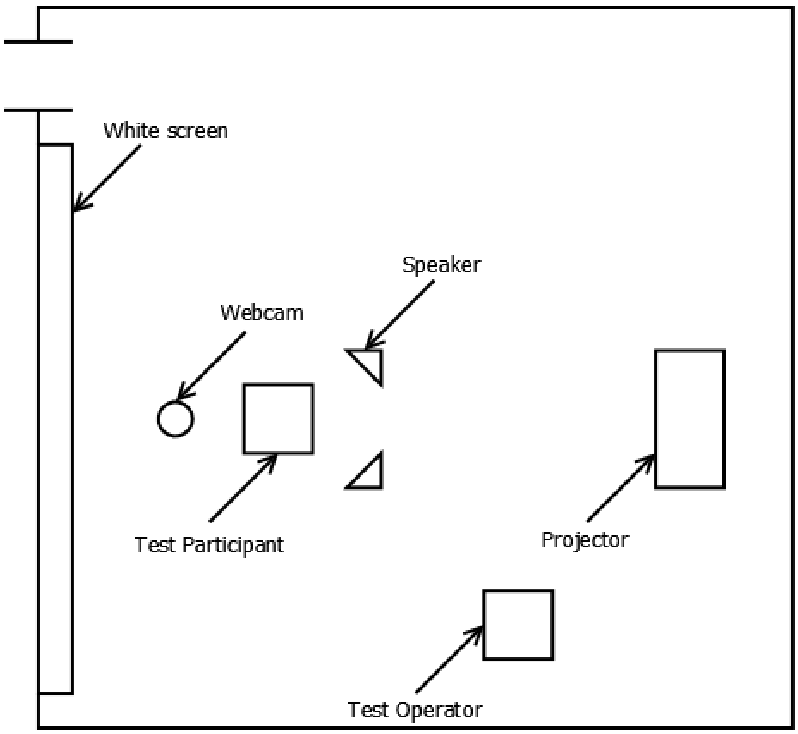

Figure 2.7: Simulator Setup

3 VEHICLE SIMULATOR STUDY

3.1 Introduction to Simulator Study and Preliminary Results

3.1.1 Test Participants

The preliminary experiments are performed on the first version of the vehicle simulator with a restricted number of 4 participants. Each one of the participants are selected according to a different driver profile to see if there is a possibility to identify each profile from the simulator test results.

The selected driver profiles are:

- Experienced driver,
- Occupied driver,
- Elderly driver,
- Teenage driver.

The experienced driver is an average but skilled driver with 20 years of driving experience. The occupied driver is the same driver as the experienced driver but he is enforced to have a conversation and to answer the question during the test drive. The elderly driver is also an ordinary driver, he is older than middle-age. The teenage driver has a driving license but his driving experience is very limited.

These drivers are selected because their data sets are the ones with the most significant results presenting the different driver behavior characteristics.

3.1.2 Driving Task

Two driving tasks are selected to perform the preliminary round of the simulator tests. These two represents the most basing driving tasks of cruising and lane changing.

The first driving task is the adaptive cruising, the driver is expected to perform a following task by adjusting the vehicle's velocity and headway distance according to the leading vehicle which is traveling with a constant velocity, (a screen-shot of cruising scenario is given in Figure 3.9).

The second driving task is the lane changing, the test driver is expected to perform double lane change maneuvering task to avoid a stationary obstacle situated in the middle lane of the freeway while oncoming vehicles with a higher velocity on the left lane may cause collision. A screen-shot is given in Fig 3.11.

3.1.3 Preliminary Results of the Simulator Tests

3.1.3.1 Test on Adaptive Cruising

The reference co-pilot system process the simulator data by using fuzzy sets as explained above and constructs a possible set of maneuvers from the fuzzyfied driver's vehicle control characteristics considering the nodes of the finite state machine representation of the maneuvering sets. An example of the fuzzy system input for this map is given in Table 3.1.

Table 3.1: Example for the First Test Drive Fuzzy Inputs

Inputs	Labels of the Fuzzy Input Variables				
HT	risky	close	close-safe	**safe**	free flow
LBSV	very near	near	approaching	far	**empty**
RBSV	very near	near	approaching	far	**empty**
LD	left dep	left	**center**	right	right dep

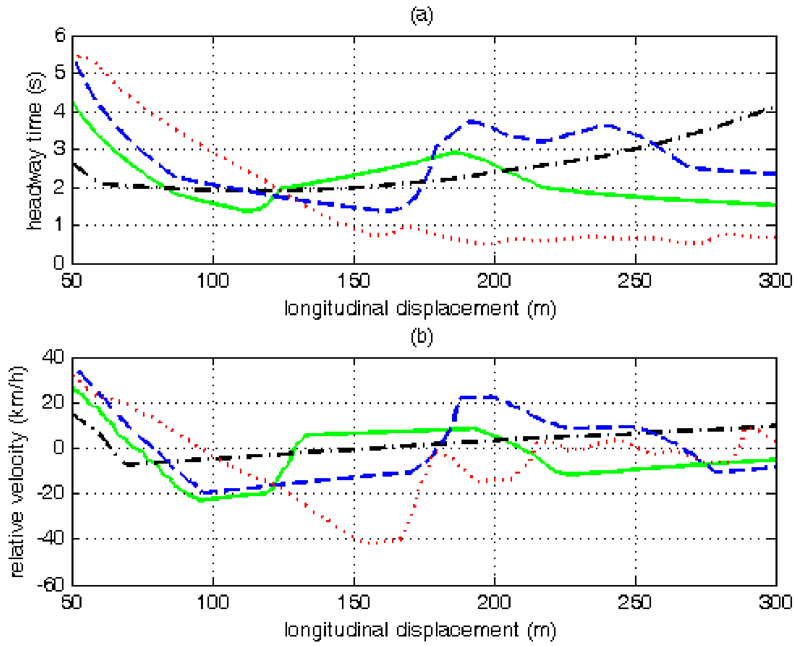

Figure 3.1: Headway Time and Relative Velocities to the Leading Vehicle. (a) Headway Time of Drivers. (b) Relative Velocity According to the Leading Vehicle

The example data is extracted from the first driver's test data. The bold written cells indicate the relevant label for the selected data. According to the input set given in Table 3.1, the possible maneuvering set consists of the following elements:

$$\Omega_1 = \{\text{FOLLOW, RLC, LLC}\}$$

The first and the second test driver follows the leading vehicle with a safe headway time, but while the first one maintains the headway time in a precise time interval, the second one drifts away after a little while, as plotted in Figure 3.1 (a). The third driver also maintains a safe headway time and when headway time is dropped below 2 seconds, the driver reacts to increase the headway time suddenly and decreases the vehicle's velocity abruptly, Figure3.1 (b), while the fourth driver performs cruising at a shorter distance leading to risky headway time.

The lateral control characteristics, represented by the estimated distance to lane departure property, of the four drivers performing a longitudinal maneuvering task are plotted in the Figure 3.2.

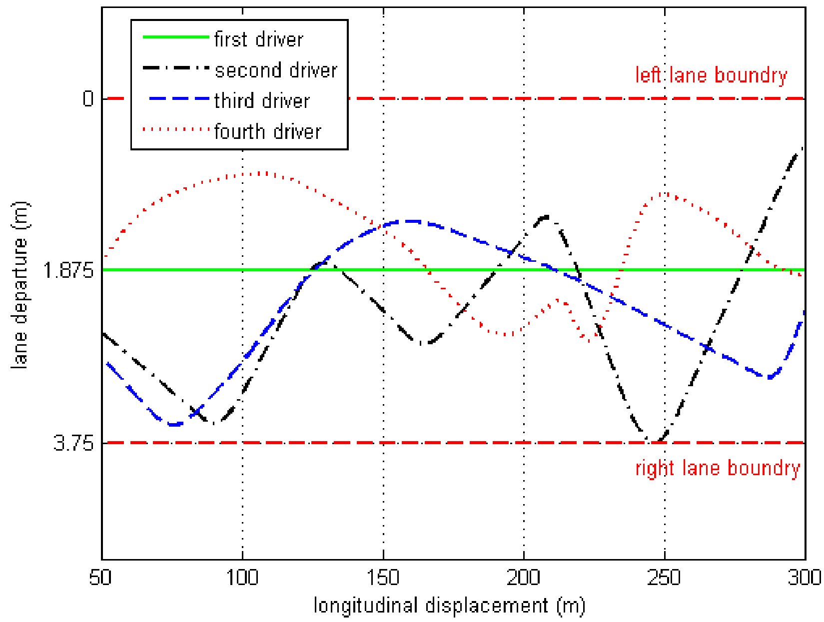

Figure 3.2: Lane Keeping Performance of Test Drivers

The first driver performs accurately by maintaining the vehicle in the center of the lane while the other drivers are somehow less responsive about the lane keeping task. The metric of the drivers obtained from this experiment is plotted in Figure 3.3.

The metric of the first driver is closer to zero whereas the second and the third one have a similar but higher performance metric. Although the performance metrics of the second and third drivers indicate that they didn't have any difficulty to complete the pursuit task, the metrics also show that the two drivers need assistance to prevent possible hazard due to potential lane departure.

The slope of the dash-dotted line of the second driver rises when the driver stops to regulate the velocity and lets the headway time increase. In the meantime, he/she also has difficulty to adjust the steering wheel angle to keep in his/her lane. The metric shows that he/she needs assistance to maintain.

The slope of the dashed line representing the third driver data rises with the sudden deceleration of the vehicle's velocity when the driver realizes that he/she is too close to the leading vehicle. It indicates that the third driver needs to be warned about the headway

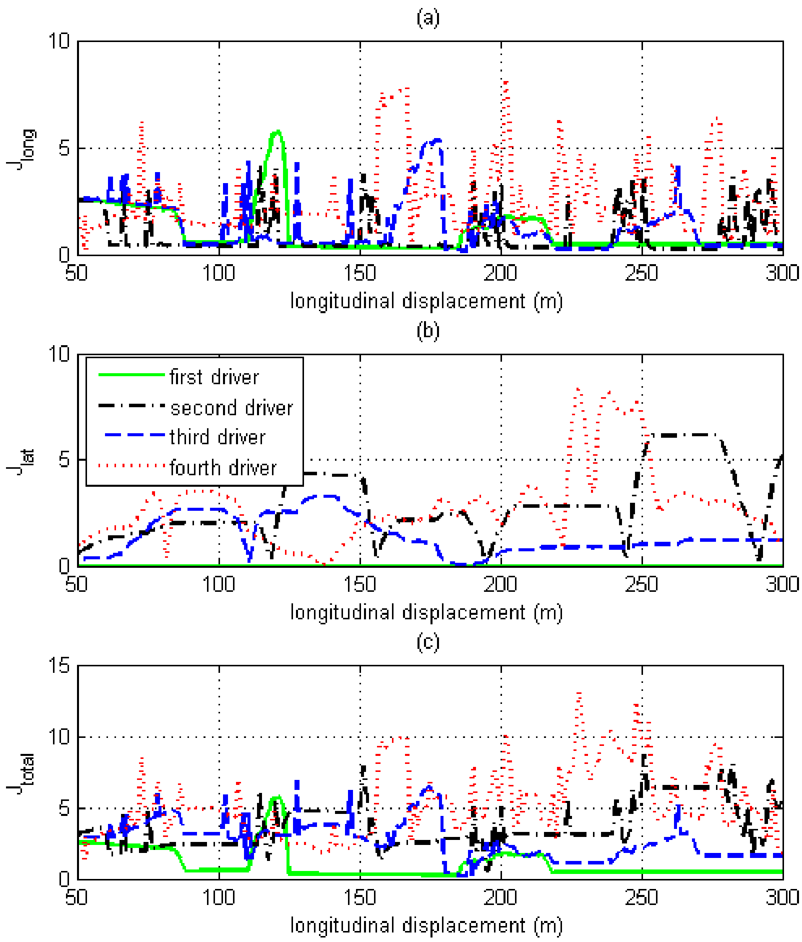

Figure 3.3: Computed Metrics of Drivers on the Cruise Driving Test

time.

The fourth driver's metric, represented by the dotted line, is the highest among all the drivers because he/she chooses to drive with a risky headway time and doesn't regulate the velocity of the vehicle accordingly, and also he/she let the vehicle shift to the left lane. The metric shows that he/she needs assistance to drive safely in the longitudinal and lateral direction.

3.1.3.2 Test on Obstacle Avoidance Maneuvering

An example of the fuzzy system input for the second map used in the test drives is given in Table 3.2.

Table 3.2: Example for the Second Test Drive Fuzzy Inputs

Inputs	Labels of the Fuzzy Input Variables				
HT	risky	**close**	close-safe	safe	free flow
LBSV	very near	**near**	approaching	far	empty
RBSV	very near	near	approaching	far	**empty**
LD	left dep	left	**center**	right	right dep

The example data is extracted from the fourth driver's test drive data just before the beginning of the left lane change maneuver. The bold written cells indicate the relevant labels for the selected data. According to the input set given in Table II, the possible maneuvering decision set for the responsive driver is:

$$\Omega_2 = \{BM, RLC\}$$

But the fourth driver does not accomplish any of the suitable maneuvers for the current situation, he/she chooses to perform a sudden left lane change maneuvering in spite of the oncoming vehicle on the left lane. The trajectory is plotted in Figure 3.4, the beginning

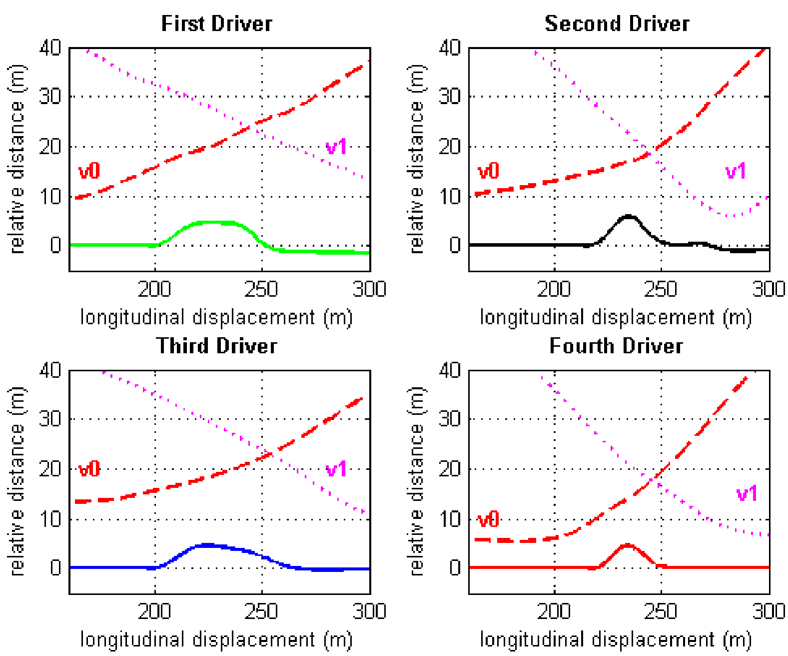

Figure 3.4: Relative Distance of Oncoming Vehicles on the Left Lane

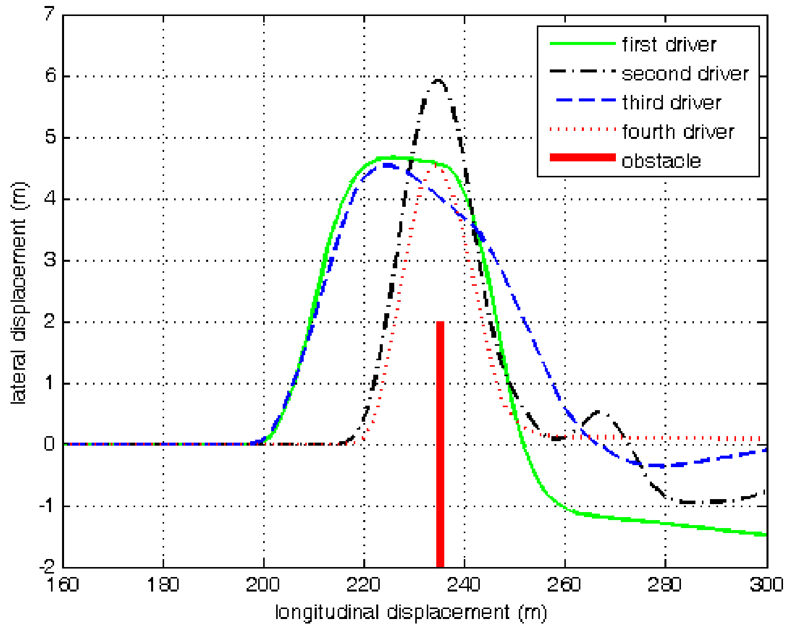

Figure 3.5: Time Responses of Trajectory in the Lateral Direction

of the lane change maneuver of the fourth driver is the nearest to the slope of the dashed line representing the first oncoming vehicle, $v0$, which is reflected on the left blind-spot.

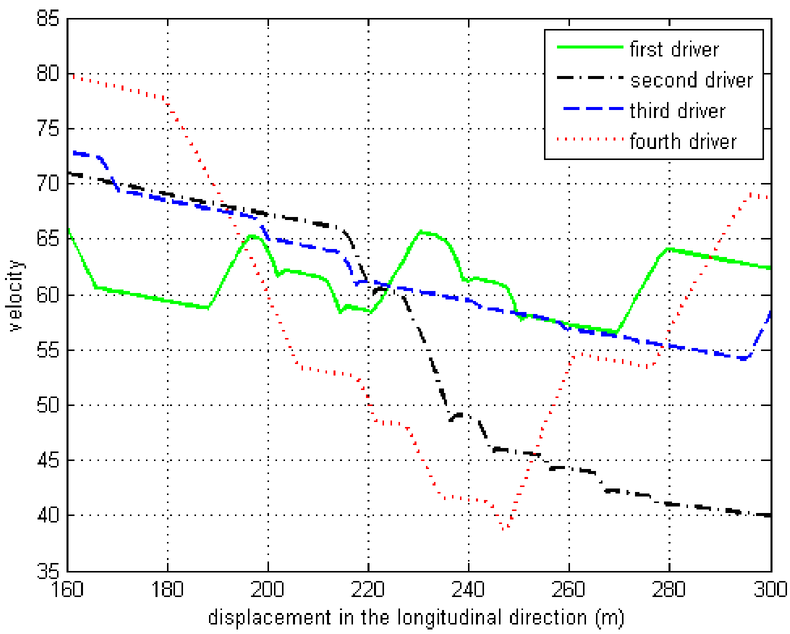

Figure 3.6: Velocity of the Vehicle Model in the Longitudinal Direction

The first and third driver performs a smooth maneuver while the second performs a sudden maneuver with a delay, Figure 3.5. The second and forth driver's vehicle velocity decreases drastically while the first and third drivers manage to perform the maneuver with more authority, Figure 3.6. Examining the computed metrics for this task, while approaching to the stationary obstacle, the first and third driver's metric increases before the other two drivers because they initiate the lane change maneuver ahead of time. Although these two drivers perform the passing task of the obstacle closer and completing the right lane change successfully while the related metric is decaying to zero again, Figure 3.7.

The difference between the second and fourth driver is caused by lane keeping performance. The second driver is causing some overshoot in lateral displacement where the

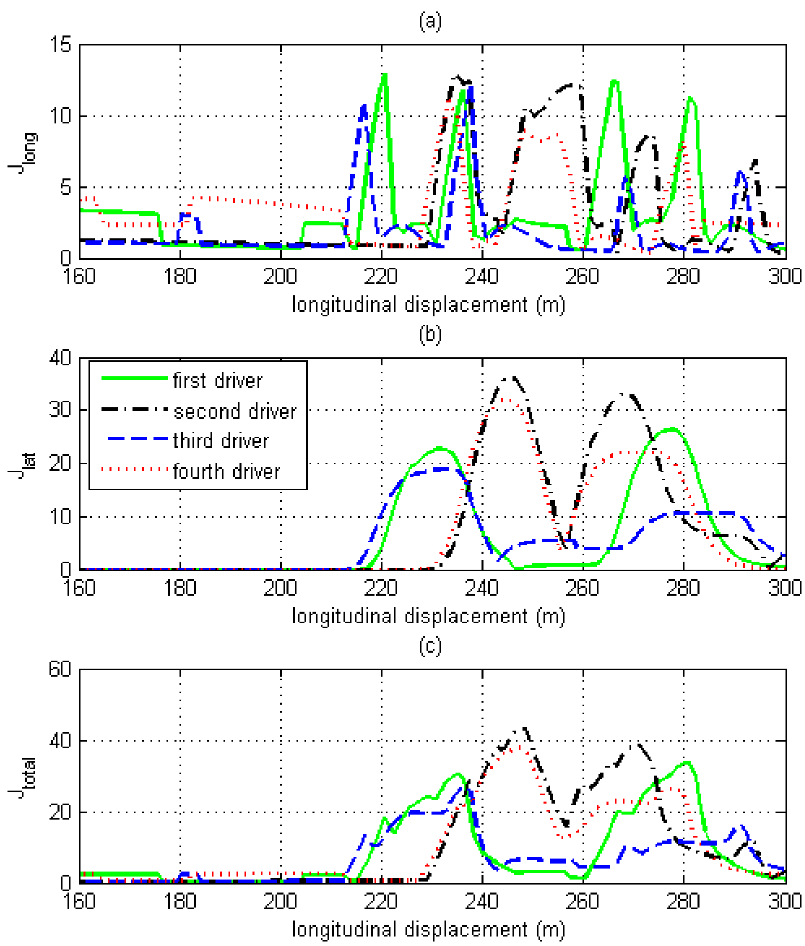

Figure 3.7: Computed Metrics of the Drivers on the Obstacle Avoidance Task

first driver is only over-steering during right lane change task. Considering large deviation of the metric, the second driver needs to be warned about the presence of the stationary obstacle situated at the center of the lane. A warning needs to be generated to attract the driver's response and attention level in the longitudinal direction of driving trajectory to adjust headway time towards safe driving conditions.

The performance metric of the third driver shows that he/she doesn't have any difficulty to perform such maneuvers.

The fourth driver's performance metric indicate that he/she has to be warned about the stationary obstacle and the oncoming vehicles form the adjacent lane but he does not have to be warned for the lane keeping maneuvering.

The results agree with the participant driver's characteristics because the first driver is an experienced and skilled driver, while the second driver is also the same test driver but he is enforced to have a conversation during the test drive. The third driver is an elderly driver in the other hand the fourth is a teenage driver.

The preliminary results are also presented in the study of Uluer et al. (2012).

3.2 Simulator Studies with 40 Test Drivers

3.2.1 Test Participants

The test drivers were chosen from a group of university students and professors with approximately similar educational background.

40 drivers with normal or corrected vision participated voluntarily in the test drives. The ratio of the female participants to the male participants is 2/3 (16 female and 24 male). The ages of the test participants are distributed in the range of 21 to 52 with the mean = 28 years and standard deviation std = 6.9 years. The age distribution of the test participants can be seen in Figure 3.8.

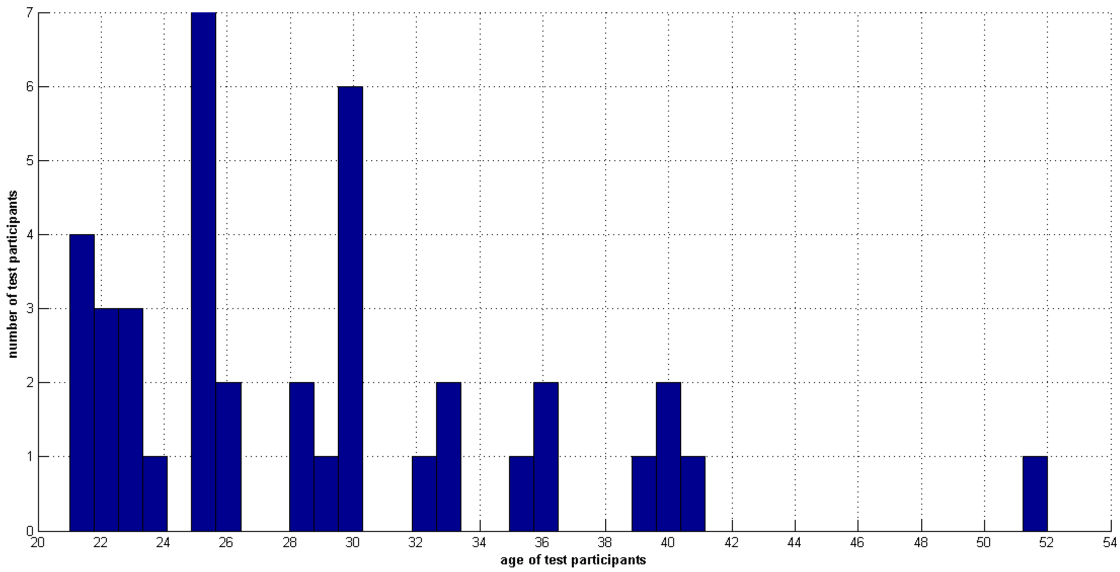

Figure 3.8: The Age Distribution of Test Participants

The test participants possess a valid driving license but their driving experience ranged from 0 to 30 years. The drivers with a driving license but without driving experience possess extensive video game experience which may have an additional training effect on hand/eye coordination capabilities. The driving experience of test participants is distributed with the mean = 4.7 years and standard deviation std = 7.1 years.

3.2.2 Driving Task

The test participants performed various driving tasks on 6 different maps. Each map were generated to simulate a different traffic situation such as pursuit of a leading vehicle, double lane change maneuver or obstacle avoidance maneuver.

Some of the maps, focusing directly the main driving task such as adaptive cruise control or lane change maneuvering, are repeated a second time with the presence of a secondary task.

The secondary task consists of handling a cell phone while driving. The cell phone distraction is selected on the purpose of diverting the visual attention of the test participant in order to create risky traffic situations.

The successful drives are recorded and the drives with accidents or unexpected situations are repeated by the participants.

The duration of the maps ranged from 1 to 4 minutes, and the total length of test drives ranged from 45 to 70 minutes according to the driving skill and choices of the test participant.

3.2.2.1 Training Map

The test participants are trained on a test map to gain experience on the simulator and to get accustomed to the simulated vehicle actuators, i.e. the steering wheel, throttle and brake pedals and lane change indicators.

The map consists of 4 part which incorporated a different traffic situation which will be featured in the other maps during the test drives.

In the first part, the driver is to follow a leading vehicle in a low-density traffic flow on a 3-lane freeway by adapting the velocity of the vehicle according to the speed limitation (50 km/h) and the headway distance. In the adjacent lanes, there are surrounding vehicles running with different velocities in the range of the current speed limitation. The lane change maneuver is optional but encouraged in order to get accustomed to the steering wheel and the use of the lane change indicator.

In the second part, the driver is to perform stop and go maneuver on a 3-lane freeway without other vehicles. The driver is told to stop at the traffic lights which turns from green to red when the vehicle driven by the test subject enters the previously defined range in the simulator configuration. The traffic lights stays red during a time interval of 7 seconds and then turns from red to green.

The third part of the test map incorporates an obstacle avoidance scenario on a 3-lane freeway where there are no surrounding vehicles and the speed limitation is 90 km/h.

The obstacles are placed to encourage the test participants for performing lane change maneuvers.

The forth part incorporates also an obstacle avoidance scenario with no other traffic and a speed limitation of 90 km/h but in this part the driver is obliged to perform consequent double lane change maneuver to avoid the closely situated obstacles.

One run on the test map lasted approximately 5 minutes. The test drivers were free to perform as many run as they wish.

The audiovisual warnings and alerts are off on the test map in order not to distract the test participant. The test driver is informed about the audiovisual warnings of the driver assistant system by the test operator along the test runs.

3.2.2.2 Adaptive Cruising Maps: f3n, f3d, f5n and f7n

Four different test drives are conducted on the same map with different constraints in order to analyze the adaptive cruising control of the test participant.

In the first adaptive cruising map, f3n, the main driving task is to follow the leading vehicle which is cruising with a constant velocity of 30 km/h. The test driver is told to maintain a safe headway distance and adjust the vehicle velocity according to the specified speed limitations (30 km/h). He/she also has to keep the subject vehicle in the lane boundaries without drifting apart and drive in the center of the lane as much as possible.

The cruising scenario takes place in dense highway traffic on a three-lane highway, see Figure3.9. The subject vehicle driven by the test participant, rolls on the middle lane of a three-lane highway. The participant isn't allowed to perform a lane change maneuver due to the dense traffic flow on the adjacent lanes.

The second adaptive cruising map, f3d, has the same specifications and constraints with the first map but in this map, the test driver has to perform a secondary task while driving.

Figure 3.9: A Screen-shot from the Adaptive Cruising Map

The secondary task is to handle a cell phone when it is notified by the test operator. With the notification of the test operator, the driver should interact with a touch screen cell phone. The secondary task consists of unlocking the screen by drawing a model (letter P) and entering a known phone number with 11 digits.

This secondary task is specially selected to distract the driver, to keep away his/her visual attention from the road and to cause hazardous traffic situations.

The third, f5n, and forth, f7n, maps are similar with the first two map but the road environment and specifications are slightly different. The main task is the same with the first map and there is no secondary task in these two maps.

The main task of the driver is to follow the leading vehicle which is cruising respectively with a constant velocity of 50 km/h and 70 km/h. The driver has to keep a safe head-way distance and adjust the vehicle velocity according to the specified speed limitation (respectively 50 km/h and 70 km/h) in a casual traffic density. The test driver is told to drive on the middle lane of a three-lane highway without performing any lane change maneuvering.

Figure 3.10: A Screen-shot from the Stop and Go Map

The purpose of the adaptive cruising maps is to collect the headway distance/time related data for each participant in order to analyze their choice of headway with and without a secondary task to perform and to observe their driving characteristics with feed-back information of the assistant system and to see their reactions to these feed-backs, if they pay any attention and correct their driving behavior or not.

3.2.2.3 Stop and Go Maps: tln and tld

The stop and go maps simulates a low-density suburban traffic on a freeway with three-lanes in each direction, see Figure 3.10. Two consecutive test runs are performed for the stop and go scenario. The first run is performed without any secondary task while the second one is performed with the cell phone distraction.

In the first run on the map, tln, the main task of the test driver is to brake and stop at the traffic lights when it turns to red and to continue driving when the light turns to green. In the mean time, the driver is also expected to maintain the vehicle in the lane boundaries and adapt the velocity of the vehicle according to the specified speed limitation (70 km/h).

The second run on the map, tld, has exactly the same specifications and constraints as the first run but with the exception of cell phone issued distraction. With the notification of the test operator, the driver should perform the secondary task of handling a cell phone while driving. The secondary task is the same with the one in the adaptive cruising maps. It consists of unlocking the screen by drawing a model (letter P) on the touch screen and entering a known phone number with 11 digits.

The test operator notifies the driver when he/she is waiting for the lights to turn green to analyze the possible difference caused by the cell phone distraction in the reaction time of the test participant.

The main purpose of this scenario is to measure the response reaction times of participants to the traffic lights which turn green to red and red to green by analyzing the pressure applied on the brake and throttle pedals with the absence and presence of a secondary task and to observe if they prioritize the secondary task instead of the main driving task.

3.2.2.4 Lane Change Maneuvering Maps: oan and oad

The obstacle avoidance scenario is simulated on three-lane freeway traffic with a dense flow of oncoming vehicles on the adjacent lanes which may cause hazardous traffic situations, see Figure 3.11. The oncoming vehicles cruise with a constant velocity on the same lane; they don't perform any other maneuver with the exception of adaptive cruising. The velocity of the oncoming vehicles on the left lane is 90 km/h while the velocity of the vehicles on the right is 50 km/h.

The subject vehicle is positioned on the middle lane of the freeway. There are no leading neither preceding vehicles on the lane of the subject vehicle, but the lane is obstructed by five stationary obstacles situated at the same distance from each other.

Two consecutive test runs are performed on the same map with the difference of distractive secondary task. The first run is performed without any secondary task while the second one is performed with the cell phone distraction. The second run with the

Figure 3.11: A Screen-shot from the Lane Change Maneuvering Map

distraction are performed with a selected group of drivers consisting of 13 participants because of the challenging structure of the map and high rate of test repetitions caused by crashes.

In the first run on the map, oan, the main driving task of the test participant is to avoid the stationary obstacles and merge into the oncoming traffic on the adjacent lanes by performing a lane change maneuver to the right or left lane by adjusting the vehicle velocity according to the velocity of the other vehicles and by maintaining a safe headway distance with the leading vehicle.

One of the major constraints of this scenario is the speed limitation specified for the test driver's vehicle. The speed limitation is 70 km/h for the subject vehicle. This limitation is set to encourage the test driver for returning the vehicle to its former lane in case of the left lane change maneuver which means to merge into the high velocity traffic (90 km/h). On the other hand if the driver performs a right left change maneuver and merges into the slower traffic flow, he/she is obliged to adjust the headway time to prevent the risky headway time alerts of the assistant system. The test drivers are encouraged to perform double lane change maneuvers but once the driver manages to maintain a safe headway distance with the leading vehicle, it is up to him/her to perform a second lane change to resume to the middle lane to drive faster or to continue driving among the slow vehicles.

In the second run on the map, oad, the test driver is notified by the test operator to perform the secondary task of handling a cell phone just after he/she manages to avoid the third stationary obstacle. The cell phone distraction plays an important part on the visual attention shifting. The change of the visual attention focus may cause risky situations which will guide the test driver to perform emergency maneuvering such as emergency brake or abrupt steering correction.

The driving measures collected in this scenario are blind-spot values indicating the distance of the oncoming vehicle from the adjacent lanes, lane change indicator which represents directly the intention of the driver, steering wheel angle, headway distance to stationary obstacle just before the start of the lane change maneuver and headway time with the leading vehicle.

The obstacle avoidance scenario is important to measure the reaction of the test participant to the possible hazardous situation issued by the presence of the surrounding vehicles and stationary obstacles. In this scenario, it is possible to monitor the human driver's authority on both longitudinal and lateral direction with or without a secondary task.

3.2.2.5 Overtaking Maneuvering Maps: otn and ota

The overtaking map simulates a suburban road with two lanes where one lane reserved for the ongoing traffic and the other for the oncoming traffic.

The map consists of a square-shaped circuit which is divided into four sections. The first and the third sections of the circuit simulate a dense flow of oncoming vehicles while the second and fourth sections simulate a lower density of traffic. All the oncoming vehicles have a constant velocity and they drive along a straight line as can be seen in Figure3.12.

The subject vehicle starts the circuit behind a slow leading vehicle. The main driving task is to follow the leading vehicle by maintaining a safe headway and to perform an

Figure 3.12: A Screen-shot from the Overtaking Maneuvering Map

overtaking maneuver when the test driver judges the traffic environment adequate for this maneuver. To perform an overtaking maneuver is optional for the test driver while it is hinted by the changes of traffic flow and speed limitation arrangements. If the driver performs an overtaking maneuver in the second section of the circuit, he/she is told to pull over and wait for the slow leading vehicle to appear in the third section for encouraging the driver to perform a second overtaking maneuver in the forth section.

Two consecutive runs are performed on this map. There is no secondary task to perform but the test is repeated two times, the first time with the assistant system off and the second time with the assistant system on.

In the first test run on the map, otn, the assistant system is off. The simulator doesn't generate any audiovisual warning or alert. There is no blind-spot detection, lane keeping assistance or overtaking assistance in the first run. In this run, the test participants decide themselves what is a safe headway distance and what distance they should keep from the lane boundaries.

The second run on the map, ota, is performed with the presence of the assistant system.

The collected parameters for these runs are headway time with the slow leading vehicle, headway distance with the oncoming vehicle at the start point of the overtaking maneuver, the overtaking assistant's alerts and time gap of the overtaking maneuver if it is performed.

The test performed on these maps contributes the sensitivity analysis of the assistant system. The collected data of the two runs allow to demonstrate the positive or negative effect of the assistant system on the human driver's responses and to examine if the driver reacts accurately to warnings generated by the system.

3.2.2.6 Persistent Double Lane Change Maneuvering Map: sln

The slalom map, sln, simulates a freeway with three lanes for each direction with no traffic. The subject vehicle is the only vehicle for this scenario. The specified speed limitation for the map is 90 km/h.

The test run on this map is performed one time with only the main driving task without any distraction cause.

The map consists of two sections. In the first section the test driver is instructed to stay in the lanes defined by the stationary obstacles which are placed to force the driver for performing consecutive double lane change maneuvers, see Figure 3.13. At the end of the first section, the driver performs a u-turn and continues to driving in the opposite direction. The second section of the map is obstructed with closely and diagonally situated stationary obstacles to push the test driver for performing persistent double lane change maneuvers in a close range.

The alerts and warnings of the assistance system are off along the map because it may cause driver distraction with all the audiovisual warnings and alerts issued by the stationary obstacles located closely by the nature of the map.

The collected parameters for this map are the steering wheel angle and the velocity of the subject vehicle. The oscillation movement of the steering wheel and the choice of the velocity emphasize the participant's driving skill and characteristics.

Figure 3.13: A Screen-shot from the Persistent Double Lane Change Maneuvering Map

The main purpose of this scenario is to evaluate the lateral vehicle control ability of the test driver by forcing him/her to perform the same maneuver repeatedly.

3.3 Experimental Results of the Simulator Tests with 40 Participants

Simulator tests are performed with 40 test participants with different skill level and driving characteristic. Each test participant performed on the same maps. The test runs which resulted with an accident aren't recorded and evaluated, and the test drivers repeated these tests until they were successful on the test.

The experimental results obtained from the adaptive cruising scenario, stop and go scenario, obstacle avoidance scenario and overtaking scenario are explained and interpreted considering the driver behavior and characteristics.

3.3.1 Adaptive Cruising Scenario

The headway time data collected from the adaptive cruising maps is one of the driver behavioral indicators which characterize the driver's authority on the longitudinal vehicle control.

The test runs on adaptive cruising are performed four times with different constraints of distraction and speed limitation. It is possible to see that some of the test drivers are affected by the distraction of the accomplishment of secondary task which increases the test participant's mental workload.

The mean and standard deviation properties of the test driver's headway time distributions can be seen in Table 3.3 and 3.4.

The test participants with ids 009, 011, 013, 016, 017, 023, 029, 034 are clearly distracted by the secondary task. Their mean headway time increases when they perform on the map with the secondary task, while they manage to maintain a similar headway time on the other three maps without the secondary task. The change of the headway time shows that the relevant participants prioritized their secondary task and they couldn't perform accurately the main driving task.

On the other hand the participants with ids 001, 002, 003, 004, 005, 018, 021, 027, 030, 040 perform similarly on all the adaptive cruising maps by maintaining a consistent headway time. This consistency shows that these participants don't prioritize the secondary task and they perform the main driving task without being affected by the cell phone distraction.

The test results also emphasize the effect of the secondary task on the test drivers. During the adaptive cruising test run with the speed limitation of 30 km/h, (f3n), the test drivers choose to maintain their headway time under 2 seconds. On the other hand, the results are not the same for the adaptive cruising map with the cell-phone issued secondary task, (f3d). The mean headway time increases to approximately 2.5 seconds, as can be seen in Figure 3.14.

Table 3.3: Headway Time Distributions of Test Participants 001 - 020

id	$\mu(f3n)$	$\sigma(f3n)$	$\mu(f3nd)$	$\sigma(f3d)$	$\mu(f5n)$	$\sigma(f5n)$	$\mu(f7n)$	$\sigma(f7n)$
001	1,472	0,172	1,494	0,299	1,284	0,378	1,148	0,616
002	1,81	0,4	1,74	0,404	1,653	0,27	1,476	0,363
003	1,675	0,648	1,675	0,338	1,763	0,469	1,63	0,376
004	1,613	0,507	1,897	0,663	1,596	0,731	1,875	1,21
005	2,015	0,815	2,227	0,536	2,804	0,628	2,31	0,665
006	3,756	1,067	1,974	0,586	2,047	0,578	1,373	0,255
007	1,858	0,388	2,575	0,832	2,365	0,515	2,119	0,266
008	2,26	0,763	3,158	0,387	2,692	0,543	1,908	0,611
009	1,51	0,176	3,563	1,07	2,275	0,162	1,557	0,269
010	2,318	0,885	2,605	0,953	2,642	0,914	1,304	1,139
011	1,84	0,628	2,549	0,784	1,943	0,529	1,679	0,301
012	1,721	0,336	2,224	0,703	1,677	0,307	1,551	0,202
013	1,55	0,386	2,269	1,236	1,271	0,331	0,964	0,15
014	1,507	0,245	1,641	0,291	1,254	0,229	1,148	0,241
015	1,959	0,764	2,69	1,429	2,319	0,394	1,535	0,587
016	2,022	0,976	3,367	1,054	1,865	0,412	1,366	0,582
017	1,621	0,311	2,983	1,571	1,444	0,531	2,116	0,797
018	1,773	0,382	1,713	0,62	1,398	0,254	1,48	0,587
019	3,077	2,974	1,893	0,761	3,098	1,157	1,478	0,804
020	2,099	2,358	2,32	0,983	1,647	0,202	1,389	0,502

The authority level of the test participants can also be inferred from the relevant headway time distributions. The difference between the test driver 001 and 029 indicates the different skill level between the two driver. This difference can be seen in the following figures.

Figure 3.15 shows that the secondary task doesn't cause any distraction on the driver 001. He manages to maintain a similar headway time on both of the maps. In the first map without the distraction, his headway time is normally distributed with mean $\mu = 1.472$

Table 3.4: Headway Time Distributions of Test Participants 021 - 040

id	$\mu(f3n)$	$\sigma(f3n)$	$\mu(f3nd)$	$\sigma(f3d)$	$\mu(f5n)$	$\sigma(f5n)$	$\mu(f7n)$	$\sigma(f7n)$
021	1,774	0,521	1,755	0,414	1,945	0,376	1,756	1,243
022	1,41	0,275	1,613	0,452	2,023	0,249	1,06	0,517
023	1,75	0,621	2,644	0,879	1,462	0,268	1,647	0,904
024	1,928	0,59	2,279	0,93	2,421	0,315	1,419	0,27
025	1,698	0,441	2,443	1,236	1,315	0,432	1,688	0,091
026	2,416	0,895	1,908	0,952	1,243	0,363	1,209	0,651
027	1,46	0,448	1,791	1,128	1,147	0,278	1,244	0,994
028	2,646	1,416	2,733	1,406	2,41	0,772	1,598	0,464
029	1,612	0,186	2,146	0,733	1,583	0,214	1,405	0,229
030	1,634	0,53	1,66	0,414	2,615	1,448	1,174	0,562
031	2,022	1,108	1,723	0,635	2,635	0,841	1,744	3,779
032	1,698	0,441	1,892	0,617	1,466	0,476	0,953	0,325
033	1,893	0,754	3,705	1,276	1,538	0,387	1,492	1,035
034	1,663	0,278	2,699	0,797	1,956	1,36	1,191	0,428
035	1,876	0,566	3,228	1,049	2,838	0,304	2,198	0,546
036	1,778	0,41	2,157	0,846	2,055	0,567	1,709	1,016
037	2,138	0,436	1,742	0,571	1,393	0,161	1,035	0,316
038	1,825	0,773	2,906	1,192	1,675	0,187	1,47	0,527
039	1,585	0,259	1,887	0,612	1,551	0,352	1,146	0,696
040	1,716	0,341	2,184	0,659	2,154	0,215	1,704	0,86

and $\sigma = 0.172$ in the range of 1.2-1.7s. In the second run on the same map with the distraction, the headway time of the vehicle is normally distributed with mean $\mu = 1.494$ and $\sigma = 0.299$ in the range of 1.2-2s.

On the other hand, the distraction caused by the cell phone can be seen in the headway time distribution of the Driver 029 in Figure 3.16.

Driver 029 performs accurately on the first run without the distraction. The headway time

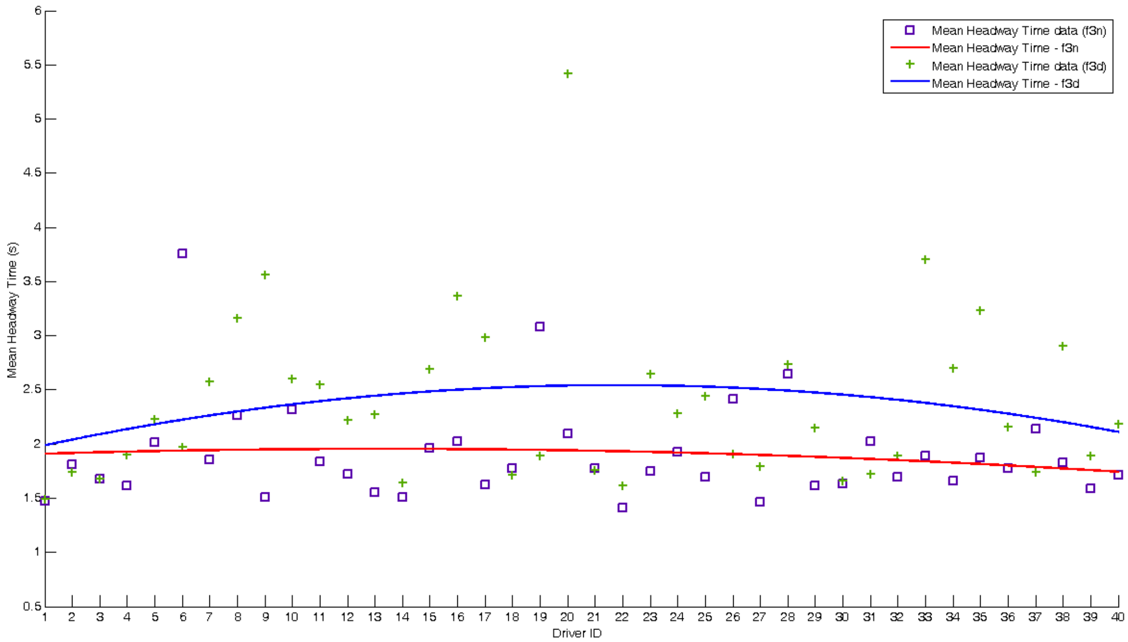

Figure 3.14: Headway Time Distributions for the Two Adaptive Cruising Maps f3n and f3d

of vehicle is normally distributed with mean $\mu = 2.416$ and $\sigma = 0.895$ in the range of 1.3 -1.9s. But in the second run with the distraction, the driver can't manage to maintain a similar headway time. The normally distributed headway time of the Driver 029 has a mean $\mu = 1.908$ and $\sigma = 0.952$ while the range of the distribution varies between 1s and 3s.

The difference between the mean and range of the two distributions shows that Driver 029 needs longitudinal assistance to perform the main driving task in the presence of the secondary task while Driver 001 doesn't need any assistance to complete his main driving task.

The test results also emphasize the difference between the male and female drivers' headway time choices. Although the slope of the mean headway time distributions show approximately the same characteristic, it is important to notice that male drivers prefer to maintain a shorter headway time where female drivers prefer to drive at a longer distance from the leading vehicle, as can be noticed in Figure 3.17.

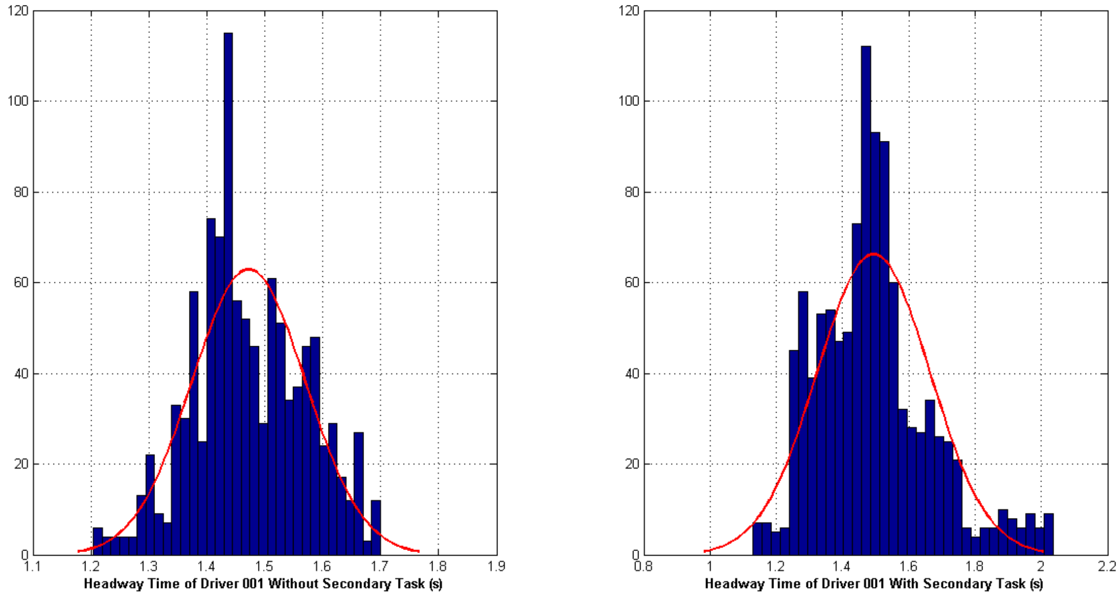

Figure 3.15: Normal Distribution of Headway Time of the Driver 001

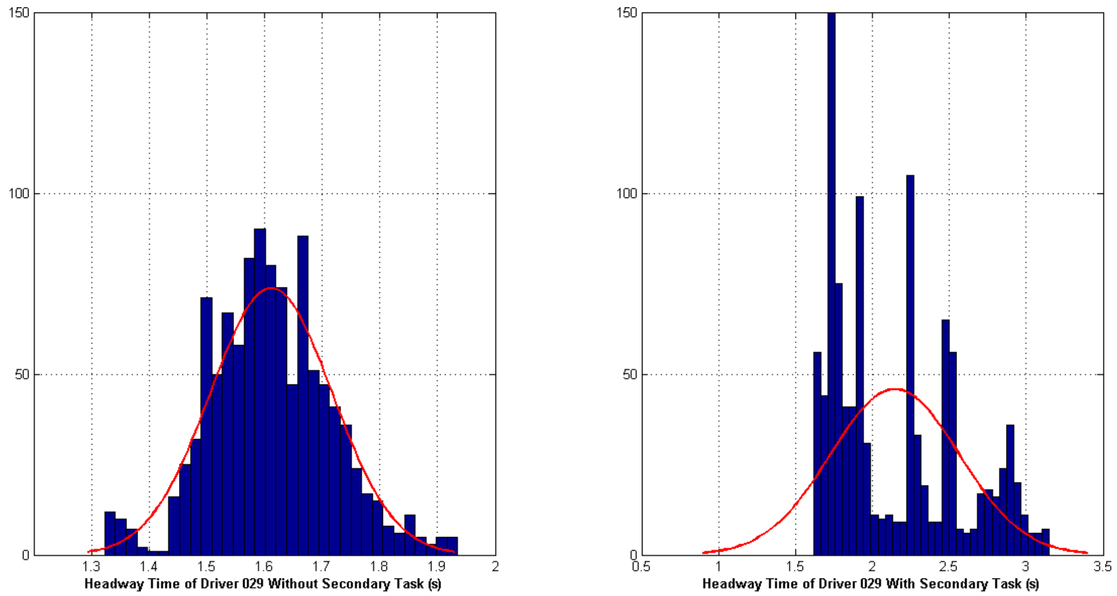

Figure 3.16: Normal Distribution of Headway Time of the Driver 029

One possible interpretation of the mean headway time distribution considering the gender of drivers, is that female test participants are more cautious than male test participants because there is a 0.5 second difference between the two curves approximating the headway time choices of the participants from the two genders.

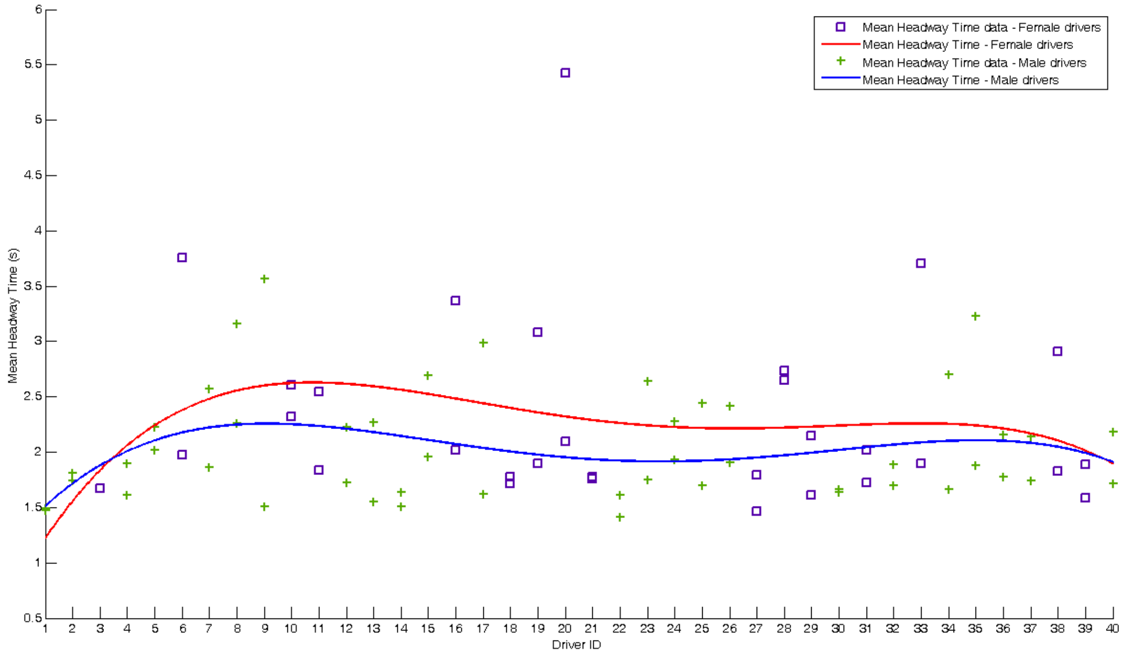

Figure 3.17: Headway Time Distribution Related to the Two Adaptive Cruising Maps for Each Gender

3.3.2 Stop and Go Scenario

Another behavioral indicator which has a great influence on the evaluation of the human driver's authority level is the reaction time.

The reaction time of the test participants are inferred from the throttle and brake pedal manipulation when the traffic light turns form green to red or vice-versa.

The reaction to red traffic light is calculated by the time difference between the time t_{red} representing the moment when the light turns red and the time when the driver applies a certain pressure higher than the specified threshold value on the brake pedal. But given the nature of the test run, the participants noticed the fact that each time they approach a traffic light, the light turns red, therefore they began to brake when they see a traffic light even before it turns to red. This situation caused inconsistency in the calculation of the reaction time. Due to this inconsistency, we preferred to work with the reaction time to green lights.

Table 3.5: Reaction Times to the 8 Traffic Lights of Test Participants 001 - 020

id	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	μ_{1-7}
001	1,3	0,986	1,936	0,674	1,422	1,204	1,069	0,859	1,227
002	0,932	0,872	0,898	0,797	0,642	1,096	1,808	3,412	1,006
003	2,321	1,102	0,809	1,365	1,068	4,801	1,358	1,239	1,832
004	2,773	1,069	1,382	1,623	0,607	1,189	0,121	1,202	1,252
005	1	0,829	1,099	0,864	0,666	1,158	1,006	1,461	0,946
006	0,634	0,917	0,742	0,701	0,632	0,998	1,125	1,37	0,821
007	0,8	1,151	0,947	0,894	0,636	1,184	0,636	1,065	0,893
008	0,933	1,305	0,938	0,649	1,147	1,198	0,879	1,003	1,007
009	1,638	0,692	0,648	0,69	0,996	1,085	1,633	1,633	1,055
010	0,705	0,731	0,68	0,644	1	0,662	1,435	1,936	0,837
011	0,71	0,823	0,93	0,691	0,765	1,261	0,909	2,201	0,87
012	0,641	1,034	0,945	0,702	0,886	0,849	0,644	1,107	0,814
013	0,858	0,602	0,529	0,334	0,502	0,388	0,705	1,98	0,56
014	1,056	0,708	0,755	0,539	0,642	0,725	0,034	1,053	0,637
015	1,302	1,187	1,296	0,992	1,133	0,833	0,623	3,251	1,052
016	1,41	1,064	1,892	0,859	1,453	1,294	1,064	3,915	1,291
017	0,622	0,641	0,917	0,669	0,863	1,155	1,501	3,233	0,91
018	0,636	1,494	1,012	0,986	0,807	0,806	2,364	1,44	1,158
019	1,226	0,928	2,911	0,937	1,003	1,061	0,878	3,857	1,278
020	0,798	0,742	0,94	0,801	1,26	1,361	0,501	2,718	0,915

The calculus of the reaction time to green is similar with the reaction to red light. It is based on the time difference between the time t_{green} representing the moment when the light turns green ant the time the driver applies a certain pressure higher than the specified threshold value on the throttle pedal. The reaction time to green of the test participants can be seen in Table 3.5 and 3.6.

The 8th column in the tables represents the reaction time in the presence of the distraction.

Table 3.6: Reaction Times to the 8 Traffic Lights of Test Participants 021 - 040

id	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	μ_{1-7}
021	5,316	0,636	0,508	0,498	0,268	0,539	0,696	0,046	1,209
022	0,803	1,54	0,703	0,631	0,815	0,634	2,411	4,812	1,077
023	1,129	1,501	1,506	9,268	0,645	0,802	-0,049	1,625	2,115
024	0,749	2,563	0,49	1,034	0,312	0,136	0,627	0,761	0,844
025	-1,254	6,218	0,555	0,005	0,622	1,435	-0,421	13,688	1,023
026	0,857	1,069	1,148	0,796	0,866	0,974	0,671	0,722	0,912
027	0,924	1,083	1,302	0,206	1,687	1,036	0,787	2,677	1,004
028	1,62	1,511	1,752	1,356	2,068	1,617	6,245	2,307	2,31
029	0,652	0,769	1,071	9,598	1,128	0,593	0,572	1,423	2,055
030	1,188	1,804	1,095	-0,25	1,093	-0,006	1,069	1,076	0,856
031	1,555	1,208	0,722	1,292	1,063	0,993	0,929	4,368	1,109
032	1,279	1,356	0,924	-2,315	0,365	0,879	1,05	1,295	0,505
033	1,221	1,93	1,468	1,438	1,203	1,214	1,14	2,009	1,373
034	1,341	1,78	0,931	0,761	1,163	0,503	1,558	-0,692	1,148
035	1,366	1,014	0,992	0,93	1,009	1,004	2,135	0,99	1,207
036	1,132	0,899	0,794	1,327	1,497	0,881	0,744	0,952	1,039
037	1,121	0,865	0,998	1,079	0,808	0,785	0,805	1,005	0,923
038	1,355	1,031	0,86	-0,07	0,414	0,642	6,454	0,72	1,527
039	0,733	1,555	1,124	1,204	0,84	0,939	1,269	0,746	1,095
040	0,634	1,117	5,029	0,063	0,401	0,376	0,996	1,767	1,231

The negative and smaller values of reaction times are caused by the fact the participant couldn't or didn't brake at the traffic light. Some of the test drivers preferred not to stop but to decrease the velocity of the vehicle slowly until the light turns to green.

While the values smaller than 0.7 seconds indicate that these test drivers are aware of the situation and respond to this situation accurately, the negative values show that the driver couldn't brake at the traffic light and continued driving.

The test participants reaction times are observed by the assumption of the reaction delay caused by the muscular functions of the human body is 0.7 s for an attentive driver, Acarman et al. (2003).

The results shows that the test drivers 002, 011, 015, 016, 017, 019, 020 ,022, 027 and 031 prioritized their secondary task and couldn't react timely when the traffic light turns from red to green. The difference between the mean of reaction times without the secondary task and the reaction time with the secondary task can be seen in the Table 3.5 and 3.6.

The mean reaction time of the drivers to the changing traffic lights without cell-phone distraction on the map tln and the reaction time of the drivers with cell-phone induced distraction on the map tld can be seen in Figure 3.18.

The points where the two lines intersect or approach each other represent the drivers who don't need any assistance. But the peaks of the red line represents the drivers

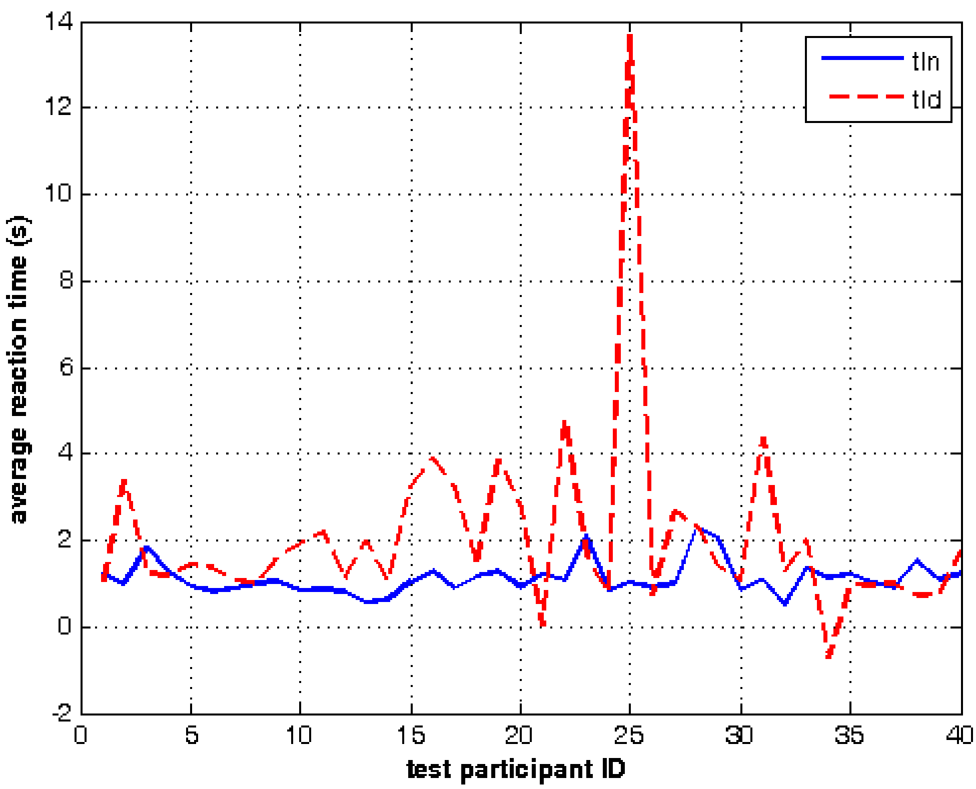

Figure 3.18: Reaction Time of the 40 Participants on Stop and Go Maps tln and tld

with a reaction delay caused by the secondary task. The delayed values of reaction time show that these drivers need assistance to perform their main driving task while the other participants don't need it considering the fact that they didn't have any difficulty in the accomplishment of the main driving task in the presence of the distractive secondary task.

3.3.3 Obstacle Avoidance Scenario

The results of the analysis on the obstacle avoidance scenario show that the majority of the participants chose to perform a right lane change maneuver and merge into the slower traffic when they have confronted the stationary obstacle, rather to perform a left lane change maneuver into the high velocity traffic.

The performance of the lane change maneuver is important to determine the authority level of the test driver because to perform the maneuver successfully, the driver has to consider various factors regarding the surrounding traffic.

The lane change maneuvers performed by Driver 011 can be seen in the Figure 3.19. The straight blue line represents the lateral displacement of the vehicle driven by the test driver while the dashed, dotted and dash-dotted lines represent the evolution of the relative distance of the ego vehicle to the surrounding ones. The red lines represents the faster vehicles on the left lane while the green lines represents the slower vehicles on the right lane.

Driver 011 performs a right lane change maneuver to avoid the first stationary obstacle and stays in the right lane. But as shown in the first figure, when the headway distance with the $v07$ decreases he performs a left lane change maneuver to resume his former lane just after he overtakes the second obstacle.

In the second figure, the driver performs again a right lane change maneuver to avoid the third obstacle. The right lane change maneuver indicates that the driver is aware of the traffic situation. As the driver gets closer to the third obstacle, the two surrounding vehicle approach from the adjacent lanes, $v07$ from the right lane and $v13$ from the left lane. The

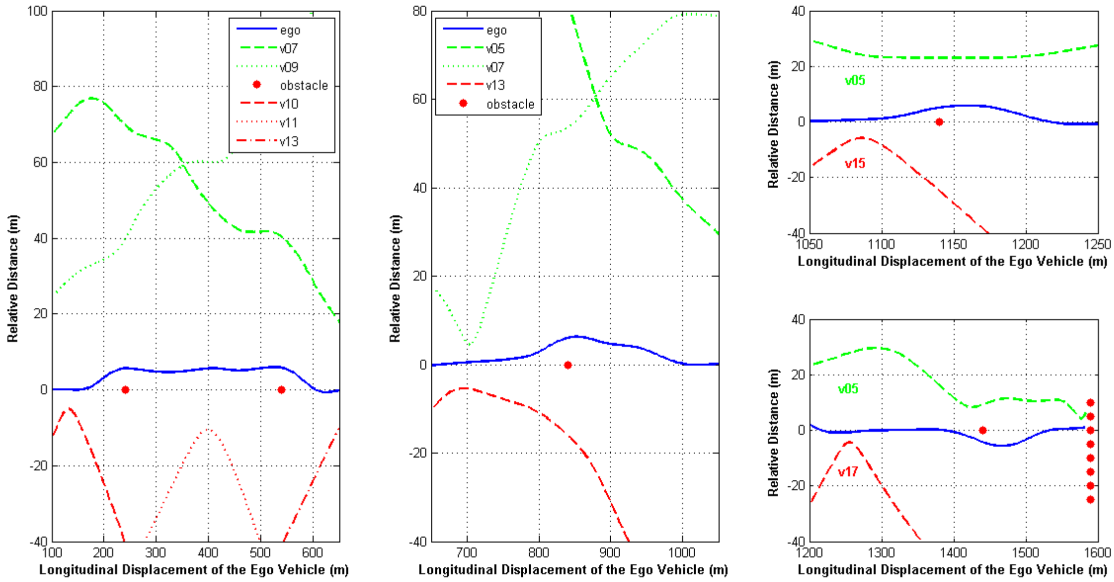

Figure 3.19: Lateral Displacement of the Ego Vehicle Driven by Driver 011 and Relative Distance of the Surrounding Vehicles during the Lane Change Maneuvers

driver prefer to perform the right lane change maneuver and merge into slower traffic and adjust the velocity of the vehicle accordingly as shown by the abrupt increase of the slope of the dotted green line which represent the relative distance between the two vehicle. On the other hand the slope of the dashed red line shows that if the driver had performed a left lane change maneuver it would probably cause a risky situation or a collision.

At the third figure, as there is an approaching vehicle form the left lane, $v15$, the driver chooses again to perform a right lane change maneuver where he manages to maintain a safe relative distance with the $v05$.

At the forth figure, the driver performs a left lane change maneuver to avoid the fifth stationary obstacle because the right lane isn't available due to the approaching vehicle $v05$ which is cruising at a close distance just before the lane change maneuver. On the other hand, the left lane is available because $v17$ is cruising at a safe distance to perform a lane change maneuver towards the left lane.

The behavioral metric of Driver 011 indicates that he doesn't need any assistance for the obstacle avoidance and he is aware of the evolving traffic situations.

3.3.4 Overtaking Scenario

The relevant data collected from the overtaking maps are headway time and following distance with the leading vehicle, overtaking duration and distance, time-to-collision to the opposing vehicle at the beginning and end of the overtaking maneuver. A summary of these variables can be found at the end of the chapter for each map of the overtaking scenario.

The headway time data collected on the overtaking maps shows the positive effect of the driver assistant system on the human driver to maintain a safe headway time with the leading vehicle. The change on the following distance also proves that the system alerts conduct the driver to maintain a safer headway distance with the leading vehicle. While the system alerts are off, the driver follow the leading vehicle at a closer distance, but while the alerts are on the drivers are warned by the system to maintain a safer following distance.

The mean values and the standard deviation characteristics of the headway time distributions of the test participants with/out the system warnings are displayed in Table 3.7.

$\mu(ht_n)$ represents the mean of headway time distribution with the assistant system warnings and alerts off and $\mu(ht_a)$ represents the mean of headway time distribution with the system on.

The headway time distribution mean values show that some of the test drivers preferred to drive at a risky or close following distance in the absence of the system warnings while the other managed to keep a safe headway time in both of the test runs.

The results indicate that Drivers 003, 004, 005, 013, 017, 021, 022, 032 and 039 doesn't need any assistance in the longitudinal vehicle control because their choices of headway time stay the same independently of the presence of a driver assistance system.

On the other hand, the results show that Driver 001, 006, 011, 014, 015, 026, 029, 030, 033, 034 and 037 needs assistance on the car-following task because in the absence of the

Table 3.7: Headway Time Distribution of Test Participants 001 - 040 for the Overtaking Scenario

id	$\mu(ht_n)$	$\sigma(ht_n)$	$\mu(ht_a)$	$\sigma(ht_a)$	**id**	$\mu(ht_n)$	$\sigma(ht_n)$	$\mu(ht_a)$	$\sigma(ht_a)$
001	0,747	0,577	1,581	0,618	021	1,515	0,545	1,671	0,49
002	3,151	0,748	1,733	0,694	022	1,63	0,747	1,706	0,739
003	1,37	0,647	1,658	0,601	023	4,327	2,906	1,995	0,837
004	1,823	1,261	1,754	0,819	024	1,471	0,9	1,997	0,808
005	1,569	1,022	1,883	0,899	025	1,17	0,349	2,317	0,977
006	1,146	0,573	1,572	0,646	026	1,017	0,991	1,791	0,821
007	2,63	0,935	1,949	0,957	027	1,922	0,86	1,501	0,758
008	1,332	0,873	1,747	1,016	028	1,492	0,715	2,263	0,684
009	1,466	1,065	3,357	0,76	029	0,86	0,625	1,932	0,515
010	0,846	0,798	2,56	0,426	030	0,915	0,748	1,583	0,674
011	0,98	0,712	1,65	0,368	031	2,709	1,164	1,932	1,055
012	3,718	2,351	2,443	0,763	032	1,418	0,648	1,653	0,592
013	1,528	0,946	1,875	0,66	033	1,112	0,754	1,733	0,741
014	0,903	0,629	1,582	0,25	034	1,198	0,836	1,726	0,631
015	1,221	1,104	1,628	0,994	035	2,396	0,977	2,395	1,057
016	3,553	1,438	2,385	1,145	036	1,538	1,1	1,914	0,859
017	1,919	1,065	1,863	0,7	037	0,839	0,633	1,516	0,52
018	1,256	0,91	1,865	0,863	038	1,63	1,075	1,93	0,619
019	1,587	0,885	1,916	0,921	039	1,738	0,94	1,906	0,963
020	1,299	1,311	1,92	0,855	040	1,386	1,016	2,152	0,918

driver assistance system warnings, they cruise with a risky headway time which is smaller than 1 second.

Another one of the most significant measures collected from the overtaking test runs is the overtaking duration data. The overtaking duration data indicates that when the system alerts are on, the drivers perform the overtaking maneuver a little more swiftly, they don't waste any time on the opposing lane and they behave more cautiously.

Another measure which emphasize the importance of the system alerts is the time to collision, (TTC), at the beginning of the overtaking maneuver. It also shows that the drivers rely on the system alerts, the time range of the TTC parameters shows that the drivers approach a little bit closer to the opposing vehicle before starting to steer in order to overtake the leading vehicle.

The test drivers' overtaking durations given the TTC to opposing vehicle at the beginning of overtaking maneuver can be seen in Figure 3.20.

The results indicate that while the system alerts are off, the drivers take their time to accomplish the overtaking maneuvering. The average time they spend on the opposing lane is increasing approximately to 4.5 seconds. But while the system alerts are on, the warnings conduct the drivers to perform a more vigilant maneuver. The average time spent on the opposing lane shortens approximately to 4 seconds. These results show that when the system alerts are on, the driver is more aware of the road environment and rely on the assistant system to complete his/her maneuver safely.

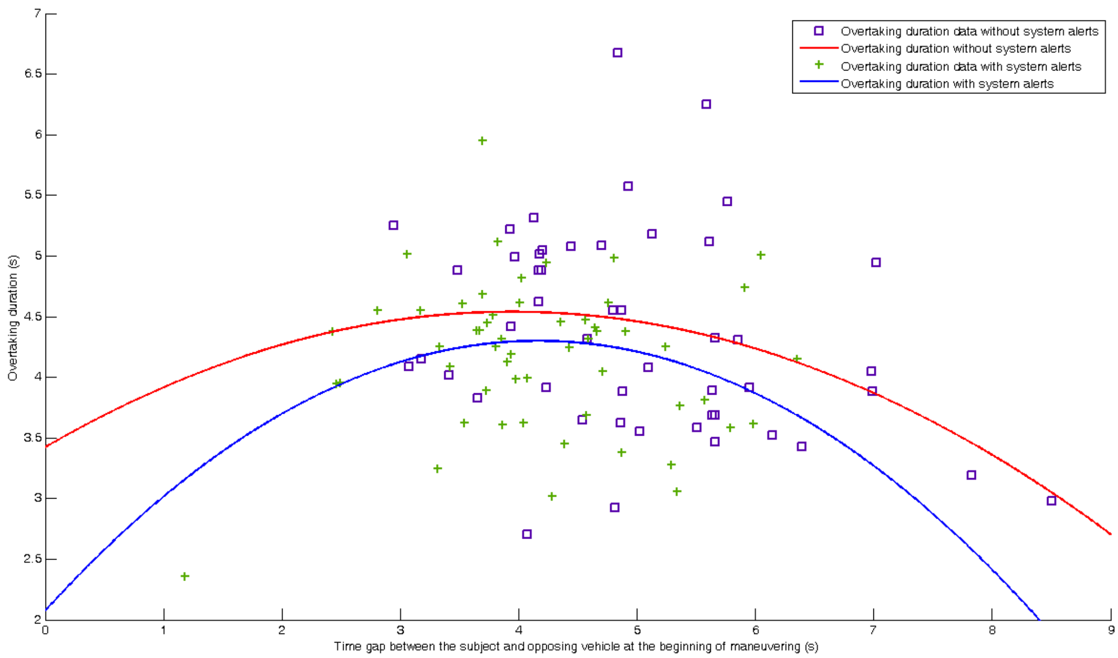

Figure 3.20: Overtaking Duration and TTC to Opposing Vehicle at the Beginning of Overtaking Maneuver

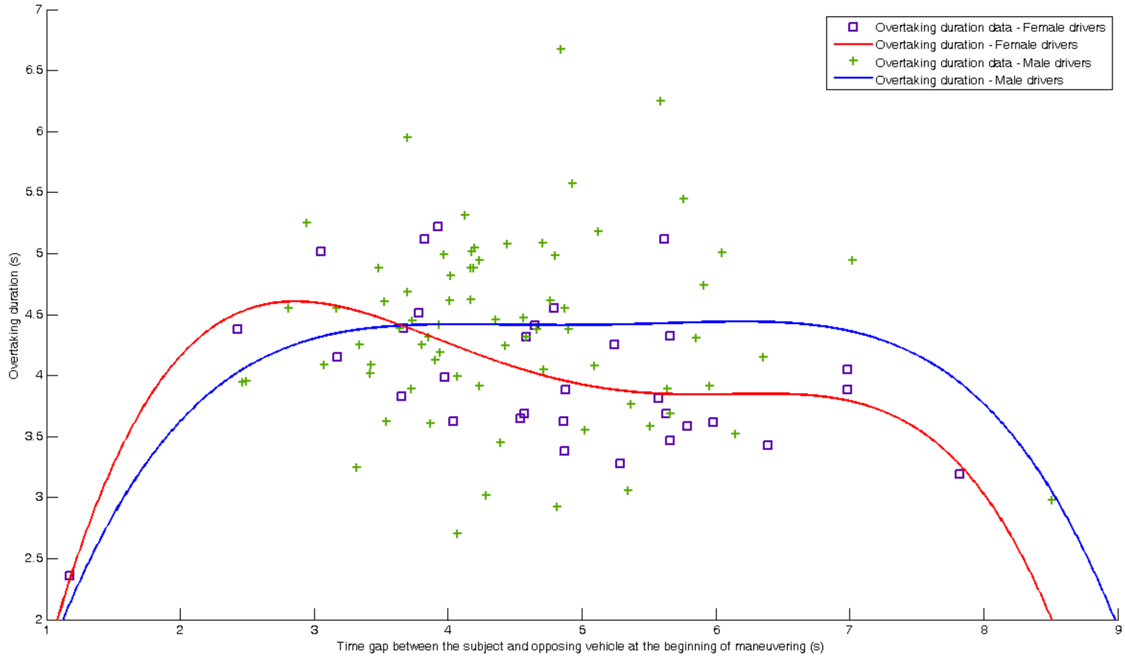

Figure 3.21: Overtaking Duration and TTC to Opposing Vehicle at the Beginning of Overtaking Maneuver Given the Gender of Test Drivers

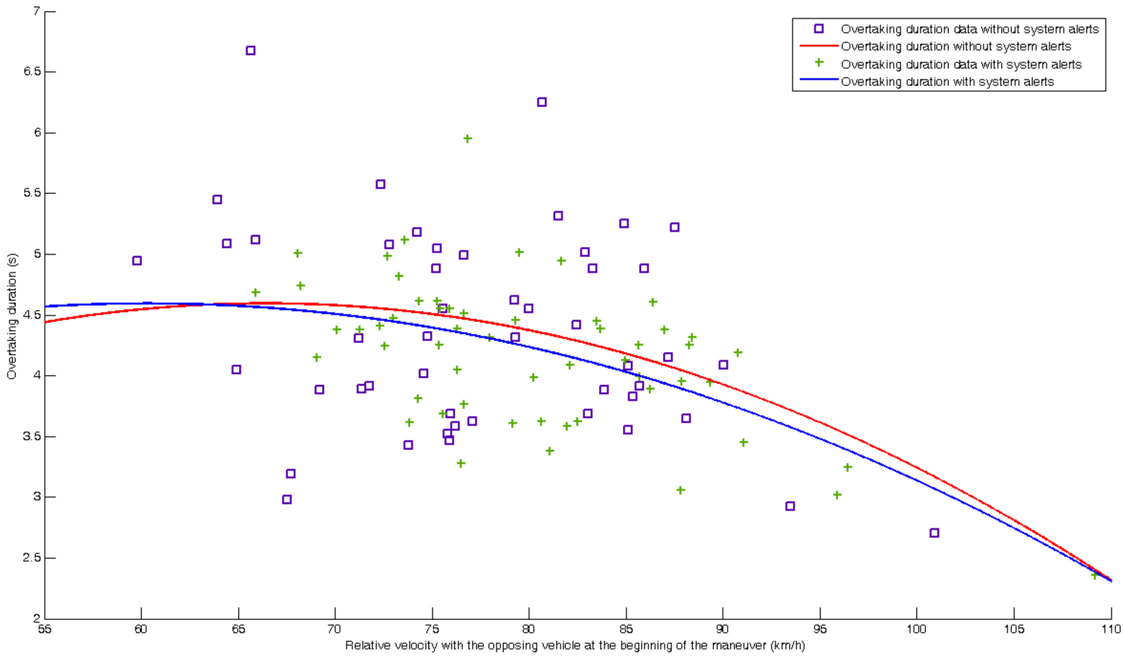

Figure 3.22: Relative Velocity with respect to Opposing Vehicle and Overtaking Duration of Test Participants

The distribution of mean overtaking duration given the gender of the drivers can be seen in Figure 3.21. These results support the results obtained from the adaptive cruising map, the red line representing the female drivers emphasizes their cautious behavior. Even if there is enough time to complete their overtaking maneuver leisurely, they chose not to spend much time and return to their lane immediately once they have completed the maneuvering task. On the other hand, the male drivers behave more at ease and they don't hurry to complete the maneuvering task.

Another significant parameter for the overtaking scenario is the relative velocity with the opposing vehicle at the beginning of the maneuver. It can be concluded that the system alerts don't have any major influence on the relative velocity, as can be seen Figure 3.22.

The overtaking test run results also show that the system alerts improve the overtaking maneuver performance among the individuals who are about the same age and share similar years of driving experience.

The four overtake maneuvering performed by the four different driver is shown in Figure 3.23. The first two trials are preformed without the system alerts while the last two trials are performed with system alerts. The four test drivers are about 40 years old and they are experienced drivers. The red and pink lines represents the female drivers with driver id 018 and 033, where the blue and black lines represents the male drivers with driver id 004 and 030.

In the figure, it can be noticed that driver 033 prefers not to perform any overtaking maneuver and follows the slow leading vehicle until the end of the test run while the driver 030 prefers not to perform an overtaking at his third trial.

It is important to note that the overtaking durations of the three drivers are decreasing with the system alerts. The results indicate that the drivers maintain or improve their maneuvering performance.

The drivers with ID 004 and 018 achieve to maintain their performance with or without the system alerts, this also gives an idea about the authority level of these two drivers, it

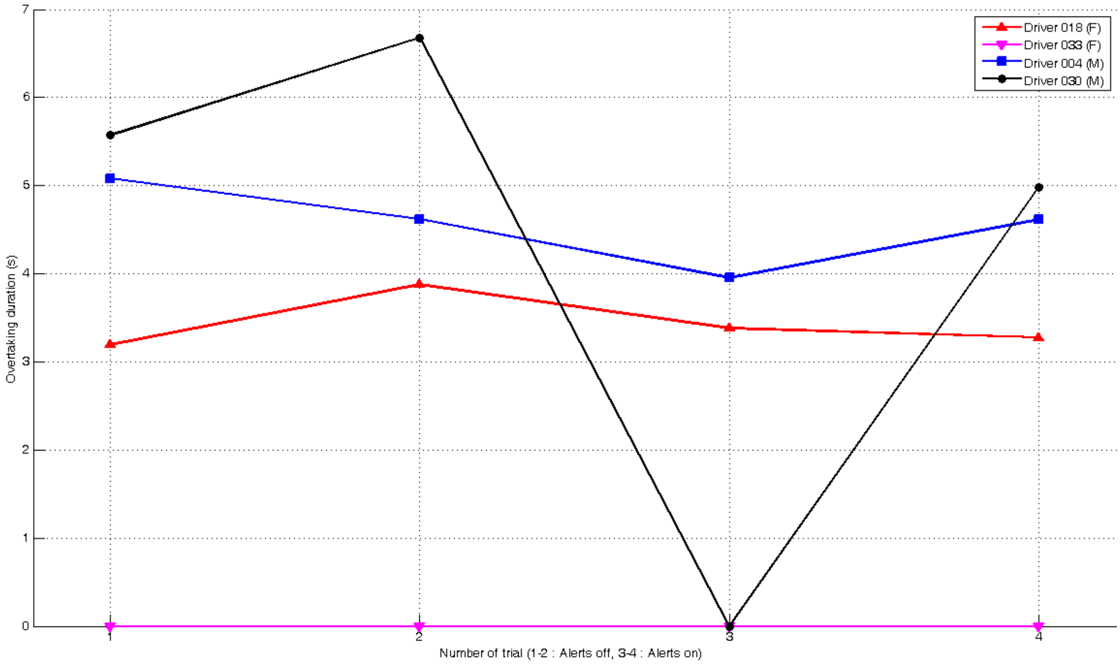

Figure 3.23: Overtaking Durations of 4 Drivers with the Same Profile but Different Gender (Experienced and Age ∼40)

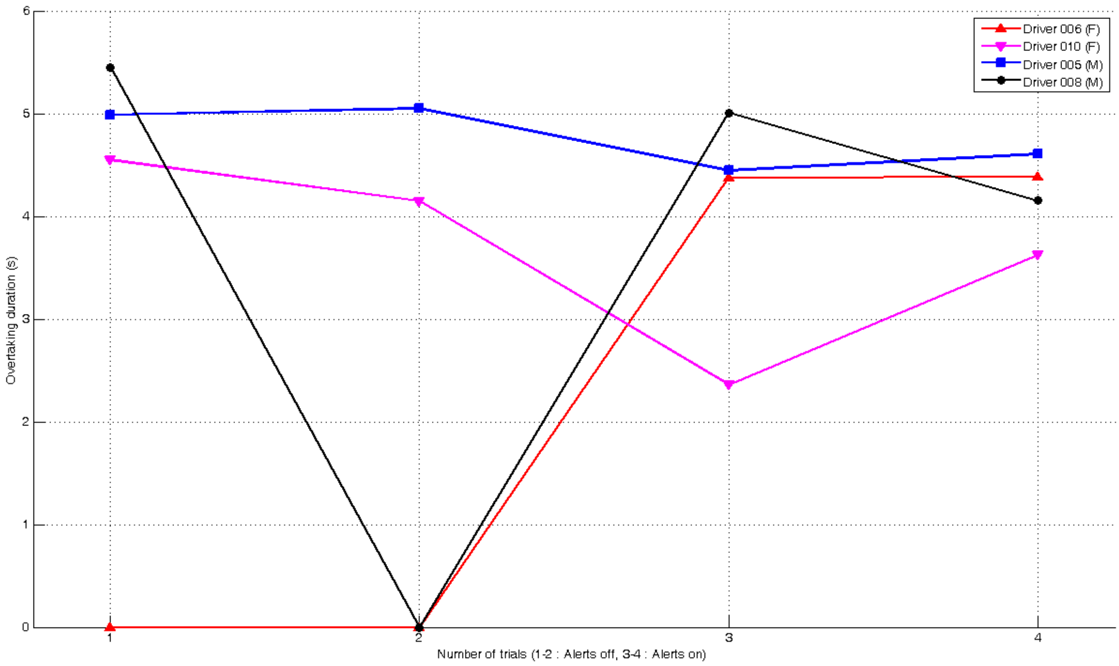

Figure 3.24: Overtaking Durations of 4 Drivers with the Same Profile but Different Gender (Novice and Age ∼25)

shows that they don't need any assistance for the vehicle control and for the maneuver. On the other hand, the overtaking duration of the driver 030 shows that he needs assistance to perform the overtaking maneuver because in his first two trials he spends longer time on the opposing lane and the time spent on the opposing lane may cause hazardous situations for the driver. But it can be remarked that his performance improves with the system alerts and he manages to perform his maneuver in a shorter time in his fourth trial.

The four overtake maneuvering performed by another set of four drivers is shown in Figure 3.24. Contrary to the first set of drivers, these four test drivers are about 25 years old and they are novice drivers. The red and pink lines represents the female drivers with driver ID 006 and 010, where the blue and black lines represents the male drivers with driver id 005 and 008.

Even though the driver profiles are different, the overtaking duration results are similar to the first set. They also show that the overtaking performance improves with the system alerts.

The driver 005 achieve to maintain his performance independently of the system alerts but the other three drivers make use of the system alerts. Especially the driver 006 who choose not to perform any overtaking in her first two trials, performs well when the system assists her. The drivers 008 and 010 also improve their performance and complete the maneuver in a shorter time when the overtaking assistance is provided for them.

The relevant data collected from the overtaking maps with/out the system alerts can be seen in Table 3.8.

Table 3.8: Summary of Relevant Overtake Maneuvering Measures with/out System Alerts

Map	Variable	Units	Mean	Std.	Min	Max
otn	Overtaking duration	s	**4,35**	0,84	2,7	6,67
	Overtaking distance	m	99,85	17,24	60,88	140,26
	Subject vehicle velocity	km/h	58,13	7,53	39,31	80,04
	Following distance	m	**18,43**	5,31	7,26	29,92
	Relative speed with leading vehicle	km/h	-20,28	8,44	-43,53	-2,43
	Relative distance with opposing vehicle	m	164,54	18,65	124,27	207,77
	Relative speed with opposing vehicle	km/h	77,66	8,44	59,8	100,9
	Time gap between the subject and the leading vehicles	s	3,85	2,69	1,64	20,67
	Time gap between the subject and the opposing vehicles at the beginning of the maneuver	s	**4,99**	1,1	2,94	8,50
	Time gap between the subject and the opposing vehicles at the end of the maneuver	s	1,94	0,96	0,18	4,54
ota	Overtaking duration	s	**4,17**	0,61	2,36	5,94
	Overtaking distance	m	101,84	13,49	74,94	134,3
	Subject vehicle velocity	km/h	61,79	7,14	47,9	85,43
	Following distance	m	**25,31**	7,3	12,46	43,02
	Relative speed with leading vehicle	km/h	-22,69	8,14	-51,8	-8,52
	Relative distance with opposing vehicle	m	153,54	20,62	89,73	182,28
	Relative speed with opposing vehicle	km/h	80,06	8,14	65,89	109,18
	Time gap between the subject and the leading vehicles	s	2,89	0,79	1,26	4,93
	Time gap between the subject and the opposing vehicles at the beginning of the maneuver	s	**4,17**	1	1,17	6,35
	Time gap between the subject and the opposing vehicles at the end of the maneuver	s	1,43	0,81	0,04	3,41

4 DEVELOPMENT OF REFERENCE CO-PILOT VALIDATION MODEL

The validation of the human driver's maneuvering behavior is one of the most critical tasks of the reference co-pilot system.

The assistant system have to infer the human driver's intentions in order to assist or to warn him/her timely and necessarily as he/she performs his/her maneuvers. For this inference task, the system has to observe and analyze the prior driving data and validate which action will be taken by the human driver. The validation is important for the system to achieve an understanding about the driving behavior of the human driver in order to evaluate his/her decisions and choices.

The reference co-pilot system monitors the driver and monitors his/her braking tendencies in the adaptive cruising scenarios and lane change maneuvering in the obstacle avoidance scenario to validate the selected maneuver's accuracy.

The braking maneuver is selected because it is the most frequent maneuver performed by a driver in real-life traffic. It is a simple maneuver but it is characteristic of a driver in terms of use of the vehicle actuators; i.e. throttle and brake pedals in the context of the adaptive cruising task.

In contrast with the braking maneuvering, the lane change maneuver performed to avoid a stationary obstacle is a more complex task. It involves a chain of actions related both to the state of subject vehicle and to the dynamics of surrounding traffic such as the oncoming vehicles from adjacent lanes.

The driver has to consider the oncoming vehicles from adjacent lanes as well as the spacing of his/her vehicle from the stationary obstacle and has to make short-term decisions to perform a safe maneuver without involving hazardous situations.

The reference co-pilot system use Bayesian networks to validate the maneuvers performed by the human driver.

Bayesian networks are widely popular in the intelligent transportation systems research studies, because they offer to reason under the constraint of uncertainty. They combine probability and graph theory which makes easier the conceptualization and the understanding of the proposed computational model.

4.1 Validation of Braking Maneuver in Adaptive Cruising Scenario

The braking maneuvers performed by the participants on the simulator tests are relevant mainly in the context of the adapting the headway time with the leading vehicle. Because according to test setup, the drivers are not allowed to perform any other maneuvering task and there is no possibility that the surrounding vehicles performs a maneuver to stress the driver.

To perform a braking maneuver, the driver should consider the velocity of the subject vehicle and the lead vehicle as well as the spacing between the two vehicles. But in the adaptive cruising scenario on the simulator tests, the velocity parameters don't represent any significant information. First of all the driver of the subject vehicle is restrained by a speed limitation, so speeding profiles of drivers are similar and furthermore the lead vehicle drives with a constant velocity which isn't interesting in terms of validation. Due to these facts the Dynamic Bayesian Network (DBN) is modeled according to the headway time choices of the test drivers which represents accurately both the velocity and spacing parameters. The headway time alerts provided by the assistant driver system is also considered to enhance the accuracy of the validation task.

The DBN that characterizes the braking maneuvering process is represented in Fig. 4.1

The model is based on the idea that the headway time alert has a direct effect on the use of the brake pedal. The headway time alerts triggered by the system results in the increasing pressure on the brake pedal. And this brake pedal activity directly influences the headway

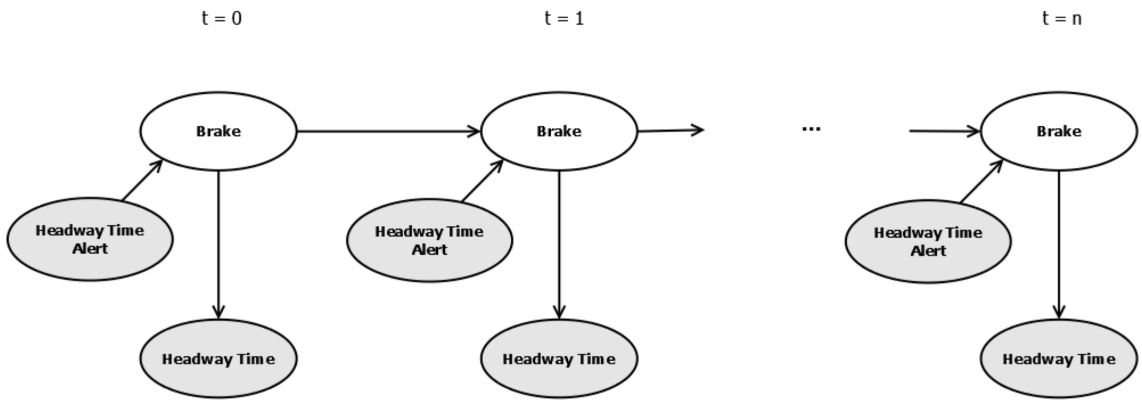

Figure 4.1: The Dynamic Bayesian Network for the Braking Maneuver Validation

time.

The variables of the DBN are discretized in order to simplify the computational cost.

The variables Headway Time Alert (HTA) is represented by two states such as $\{$on, off$\}$, as well as the Brake (B) variable. And accordingly two states $\{$safe, risky$\}$ represents the Headway Time (HT).

Initially we assume that we don't know the state of the brake pedal position if it is on or off. So we assign equal probabilities to each one of the two possible states, the initial belief matrix is as follows:

$$bel(Brake) = \begin{bmatrix} 0.5 \\ 0.5 \end{bmatrix}$$

where the first row represents the probability that the brake pedal is on and consequently the second row represent that the brake pedal is off.

We characterize the conditional probability between the Headway Time (HT) and Brake (B) as follows:

$$p(B|HT) = \begin{bmatrix} 0.4 & 0.6 \\ 0.6 & 0.4 \end{bmatrix}$$

In Equation 4.1, the first column represents the safe headway and consequently the second represents the risky one; and the first row represents that the brake is on while the second represents it is off. We assume that if the headway time is safe, it is more likely that the driver doesn't brake and if the headway time is risky the driver will have to brake.

And finally the conditional probability characterizing the time-dependent relationship between the two consecutive nodes of the Brake variables is given according to the different observed states of the Headway Time Alert (HTA) variable and it is as follows:

$$p(B_t|HTA = on, B_{t-1}) = \begin{bmatrix} 0.9 & 0.9 \\ 0.1 & 0.1 \end{bmatrix} \tag{4.1}$$

$$p(B_t|HTA = off, B_{t-1}) = \begin{bmatrix} 0.5 & 0.5 \\ 0.5 & 0.5 \end{bmatrix} \tag{4.2}$$

Similarly the other matrices, the first column represents that the variable B_{t-1} is on, while the first row represents that the B_t is on.

In Equation 4.1 we assume that if the driver is braking at time $t-1$, he/she will continue to brake at time t if the headway time alert is on and likewise even if he/she isn't braking at time $t-1$ he/she will start to braking immediately at time t if the headway alert is on.

In Equation 4.2 we assume that if the headway alert is off, the driver is free to use the brake pedal so the probabilities is distributed equally.

At each time step, the system use the state of Headway Time Alert (HTA) variable and the prior belief calculated at the previous time step to configure the posterior belief. And then it incorporates the state of the Headway Time (HT) and changes the belief matrix accordingly.

The relevant steps of the updating algorithm of the network can be represented as follows:

$$\overline{bel}(Brake_t) = \sum_{Brake_{t-1}} p(Brake_{t-1}|HTA_{t-1}) bel(Brake_{t-1}) \tag{4.3}$$

$$bel(Brake_t) = \eta p(HT_t|Brake_t)\overline{bel}(Brake_t) \tag{4.4}$$

where η is the normalizer in the Equation 4.4.

The network is initialized by the same probabilities but the probabilities evolves with time according to the driving characteristics of the drivers.

The network is trained by the first adaptive cruising task map, f3n, data and it is tested on the same map and with the second map f3d which is identical to the first map except the distractive cell-phone handling task.

The validation results for the 2 test drivers can be seen in Fig. 4.2 and Fig. 4.3.

As seen in Fig 4.2, the driver with id = 003 performs six braking maneuvers during his/her simulator test. It can be noticed that the system can validate all of these maneuvers within a short time window.

The white areas in the graph of validation indicates that the highest probable action to be taken, for this example it means that the driver will perform a braking maneuver. The areas with a lighter gray color represent the second probable action whereas the black areas signifies it is the least probable action to be taken.

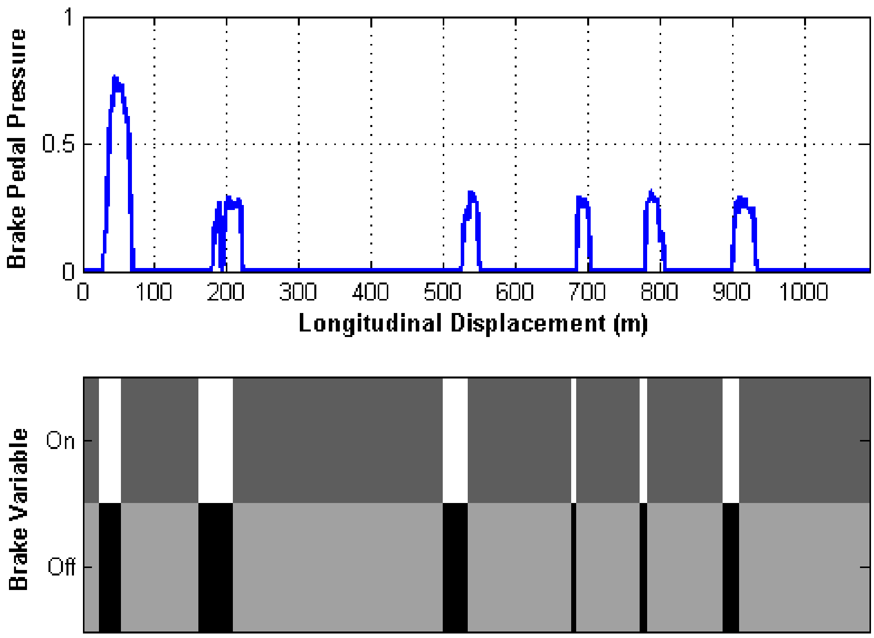

Figure 4.2: The Responses of Brake Pedal Pressure and the Posterior Probability of the Braking Maneuver for Driver 003

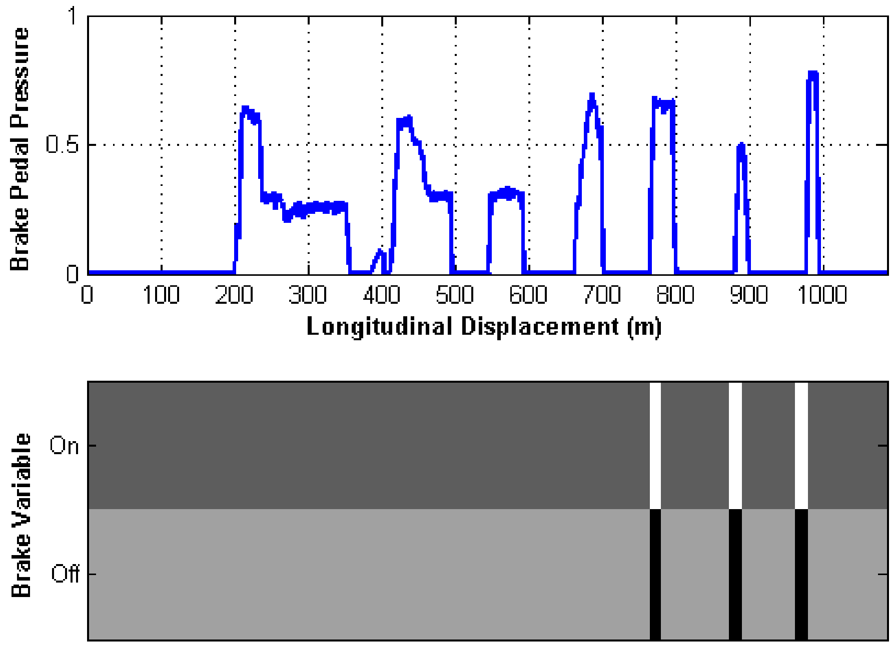

Figure 4.3: The Responses of Brake Pedal Pressure and the Posterior Probability of the Braking Maneuver for Driver 019

The validation results can be successful in terms of the abrupt braking maneuvers but it isn't accurate when there is a long-term pressure on the brake pedal. As can be noted in Fig. 4.3, the system doesn't have any difficulty to validate the last three abrupt maneuvers of the Driver 019, but it is not able to validate the other maneuvers which are distributed in a longer time window.

The validation results are given in Table 4.1.

Table 4.1: Validation Rates for the Two Adaptive Cruising Map

f3n		f3d	
True Positive 85	False Positive 28	True Positive 59	False Positive 35
False Negative 10	True Negative 91	False Negative 6	True Negative 62
Sensitivity 0.8947	Specificity 0.7647	Sensitivity 0.9219	Specificity 0.6392

The validation results show that the reference co-pilot can validate the driver's braking maneuvers accurately. The results on the f3d map emphasize that the system can validate when the driver will brake, it is important to note that the sensitivity of the test map, (f3d), is higher than the training map, (f3n).

4.2 Validation of Lane Change Maneuver in Obstacle Avoidance Scenario

The lane change maneuvering of the obstacle avoidance map is a complex maneuver, the driver is conducted to make abrupt decisions and take short-term actions to avoid the stationary obstacle and to merge into the ongoing traffic on adjacent lanes.

To perform a lane change maneuver in order to avoid a stationary obstacle, the driver has to consider his/her own vehicle's velocity and the spacing from the obstacle, as well as the velocities of the oncoming vehicles on adjacent lanes and relative spacing with these vehicles.

Considering all these facts, we use the following traffic variables to model the lane change maneuvering behavior of the driver:

- Left Blind-Spot Values (LBSV),
- Time to Collision (TTC),
- Right Blind-Spot Values (RBSV).

The variables LBSV and RBSV are the blind-spot values used by the assistant driver system to warn the driver about the approaching vehicles from adjacent lanes. These variables represent both the relative spacing and the velocity of the surrounding vehicles. The variables can take different values starting from 0 to 4. If the variable takes the value of 0 then it means that there are no oncoming vehicle on that lane, if it takes the value of 4 then it means that there is a vehicle at a really close distance on that lane. These variables are also discretized for the purpose of computational simplicity. The values 0 (empty), 1

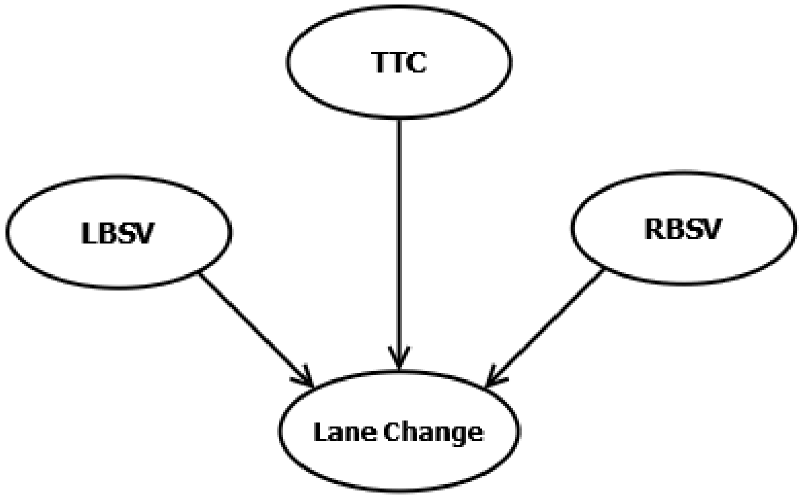

Figure 4.4: The Bayesian Network for the Lane Change Maneuver

(far), 2 (approaching) are classified as safe where as the values 3 (near) and 4 (very near) are classified as risky.

The other variable considered in the calculation of the model is time to collision (TTC) of the subject vehicle to the stationary obstacle. Similarly to the blind-spot values, this variable reflects also the velocity and the spacing of the subject vehicle from the obstacle.

It is also discretized with two states; {safe, risky}. The TTC probabilities are computed according to the driving characteristics of the test drivers, it is calculated for each driver separately by the use of the simulator data. To calculate the TTC for each driver the system considers the statistical data of their past maneuvers to determine the threshold which will be used in the calculation of the probability matrix for each driver.

The Bayesian network representing the lane change maneuver is shown in Fig 4.4.

The lane change variable seen on the Fig. 4.4 represents the probability of an intended maneuver or the decision for not performing any maneuver. The variable is discretized in 3 states. The driver may choose to perform a left or right lane change maneuver but we have to consider also the situation when he/she decides to not to perform a lane change and maintains on the actual lane if there isn't any obstacle at a risky time-to-collision.

Table 4.2: Table of Conditional Probability Related to the Lane Change Variable

	TTC=0				TTC=1			
	RBSV=0		RBSV=1		RBSV=0		RBSV	
	LBSV=0	LBSV=1	LBSV=0	LBSV=1	LBSV=0	LBSV=1	LBSV=0	LBSV=1
Left	0.3	0.1	0.45	0.1	0.45	0.3	0.6	0.4
No	0.4	0.45	0.45	0.8	0.1	0.1	0.1	0.3
Right	0.3	0.45	0.1	0.1	0.45	0.6	0.3	0.4

The joint probability equation of the Bayesian Network can be written as:

$$\begin{aligned} p(LBSV, TTC, RBSV, LC) = \quad & p(LC|LBSV, TTC, RBSV) \\ & \times p(LBSV)p(TTC)p(RBSV) \end{aligned}$$

The TTC probabilities are computed individually for each driver from the simulator data under the consideration of all the past lane change maneuvers.

The LBSV and RBSV probabilities are also extracted from the simulator study. For the obstacle avoidance map we assume that right lane is safer than the left lane because the vehicles on the right drives with a constant velocity similar to subject vehicle.

The related conditional probability table of the lane change variable can be seen in Table4.2, where the value 0 signifies it is safe and the value 1 signifies that it is risky.

It is important to note that we assume if the TTC is safe enough, the driver can decide not to perform a lane change maneuver till the TTC becomes risky.

The validation results for 2 test drivers can be observed in Fig. 4.5 and Fig. 4.6.

As seen in Figure 4.5, the driver with ID = 032 performs a left lane change maneuver when he/she is confronted with the stationary obstacle represented as a red dot in the first graph. The probability distribution shows that the system can validate this maneuver in a short-term, just before the driver starts to steer for the maneuver. The white area shows that left lane change maneuver is the most probable and the least risky maneuver to perform considering the actual traffic environment. The black areas on the center and at the right

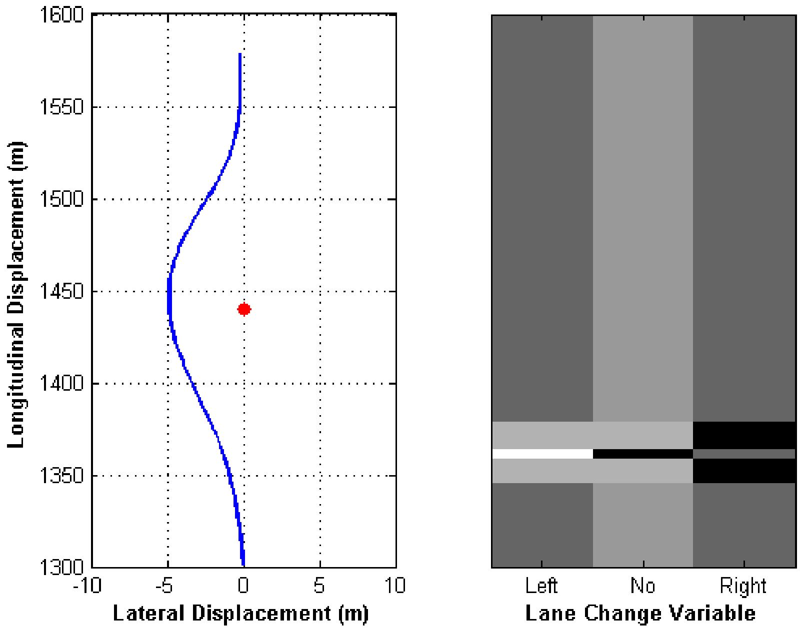

Figure 4.5: The Lateral Displacement of the Vehicle Driven by Driver 032 and the Posterior Probability of the Lane Change Maneuver

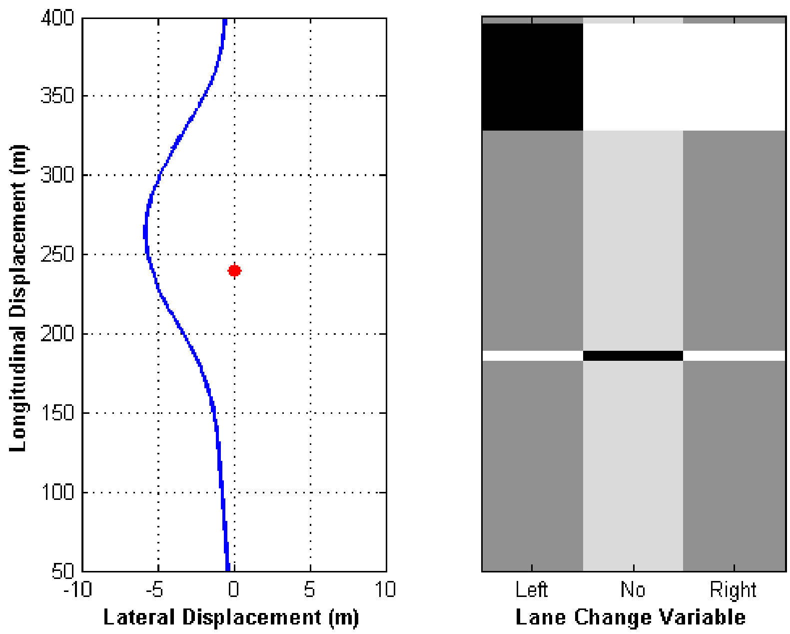

Figure 4.6: The Lateral Displacement of the Vehicle Driven by Driver 034 and the Posterior Probability of the Lane Change Maneuver

represents the most risky situations. One can conclude from the validation results that the right lane is occupied by an oncoming vehicle which will cause a hazardous situation if a right lane maneuver is performed.

As seen in Figure 4.6, the validation results can not decide if the two lanes are empty and it is safe to perform a lane change maneuver to the left or to the right. The white areas on the probability graph show that both of the two lanes are favorable for a lane change maneuvering where the black rectangle indicates that the driver is getting closer to the obstacle and the risk of collision is increasing for him/her.

One has to note that if the system calculates the same probability for two different states, i.e. if the validation results say that the risk of the performing a left lane change is the same with a right lane change, then the driver has to decide which maneuver to perform. Therefore we consider that these situations are validated correctly in the confusion matrix in Table 4.3. There are a total sum of 69 situation where the system leaves the driver to decide for performing either a left or a right lane change maneuver. The majority of the drivers, 44 of 69 situations, choose to perform a right lane change whereas the rest decides to perform a left lane change. This tendency in the lane change maneuver can be included in the validation algorithm if it isn't convenient to leave the choice to the driver.

The confusion matrix of the validation results for the lane change maneuvering is as follows :

Table 4.3: The Confusion Matrix for the Validation Results of Lane Change Maneuver

		Validated		
		Left	No	Right
Performed	Left	50	10	1
	No	0	27	0
	Right	8	16	88

The results show that the system can separate the probabilities of a left lane change from a right lane change and vice versa, but it has some difficulties to differentiate a left or right lane change from the probability of a no lane change maneuver when the value of TTC is safe. The system performance can be enhanced by the existence of the stationary obstacle. Even if the driver maintain the TTC safe, the system should know that the no lane change maneuver isn't probable around the obstacle.

5 CONCLUSION

Control authority of the driver is the key to perform the maneuvering tasks and avoid possible hazards ahead of time. Therefore evaluation of multi-modal driver, adaptation to his/her situation awareness and responsiveness is important at generating timely active safety messages without overloading the driver.

In this study, a multi-modal adaptive driver assistance system is presented. A reference co-pilot driver model is developed to monitor the driving behavior and characteristics of the human driver. An evaluation metric is presented to interpret the driver's responses with respect to the traffic situations. The situations are interpreted by the co-pilot system using simple fuzzy rules. Driver's response and decision taken about the possible maneuvering tasks are applied to the finite state machine constituted by the possible maneuvering tasks.To validate the feasibility of the presented model, tests are performed on a vehicle simulator. A simulator study is preferred because of the possibility to repeat the tests with the same traffic conditions with different drivers.

The possibility of the presented brief evaluation system towards deployment of an adaptive and multi-modal driver assistance system, is illustrated by the preliminary evaluation of a sampled set of 4 drivers. In the light of the preliminary results, a second set of simulator tests are performed by 40 test drivers with different age, different driving experience and skills.

The data collected from the 40 participants of the simulator tests, is used for the reference co-pilot driver system in order to achieve an understanding about the authority level of the human driver. The results show that it is possible to conceive an assistant system which can characterize the difference among the drivers and decide when it is necessary to warn the human driver.

To monitor the human driver maneuvering intents a validation algorithm using a simplified probabilistic model is proposed. Bayesian networks are used for providing the algorithm for the braking and lane changing maneuvers.

The system can monitor and validate which action will be taken by the driver in a short-term window and it regulates the system warnings considering the current performance of each one of the drivers individually. The used validation algorithm is discretized in time domain in order to simplify the computational load but it can be adapted for continuous input variables to achieve a better validation performance and to individualize each driver in their driving context.

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