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Secondary tasks in steady state car following situations

Master's Thesis in the Master's programme of Automotive Engineering

ANDRE FERNANDEZ

Department of Applied Mechanics
Division of Vehicle Safety
CHALMERS UNIVERSITY OF TECHNOLOGY
Göteborg, Sweden 2011
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Steady state car following situation. View from the dashboard of the following vehicle.

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ABSTRACT

Naturalistic driving studies and field operational tests are important tools for traffic and road safety research. Naturalistic driving data and accident data show that rear-end collisions are the most common type of accident in car following situations. Furthermore, distraction from secondary- tasks-has been shown to be one of the leading causes of rear-end collisions.

The aim of this thesis was to analyze driver behaviour in car following situations in order to gain insight into the influence of factors such as secondary tasks to the likeliness of rear-end collisions. A steady state car following scenario was defined and used to extract data representing car following situations from commutes on main arterial road segments. This data was studied to determine the effects of secondary tasks on driver behaviour measured by, among other variables, headway time to the lead vehicle. Driving data from passenger vehicles in the euroFOT project –the largest ongoing field operational test in Europe— was used in this study.

The results presented in this thesis indicate that traditional measures of longitudinal and lateral control such as lane position and headway time are less affected by secondary tasks than measures related to driver control inputs such as peak steering angle acceleration in steady state following situations.

Key words: Traffic safety, naturalistic driving study, field operational test, car following, secondary tasks.

Contents

ABSTRACT	I
CONTENTS	III
PREFACE	V
1. INTRODUCTION	1
1.1. Background	1
1.2. Literature review	3
1.2.1. Car following and headway time	3
1.2.2. Secondary tasks	4
1.3. Naturalistic driving data, field operational tests and EuroFOT	5
1.4. Aim	6
2. METHOD	7
2.1. Road segments	8
2.2. Drivers	9
2.3. Independent variables	10
2.3.1. Secondary task variables	11
2.3.1.1. Mobile telephone use	12
2.3.1.2. Conversations and passenger related activity	12
2.3.1.3. Eating	12
2.3.1.4. Grooming	12
2.4. Data processing	12
2.5. Preliminary data processing	12
2.6. Extraction of steady state car following data	13
2.6.1. ACC	14
2.6.2. Speed of subject vehicle	14
2.6.3. Lane changes and lane change residuals	14
2.6.4. Lead vehicle cut –ins/cut – outs	15
2.6.5. Range to lead vehicle	15
2.6.6. Segment length	15
2.7. Assumption of independence	15
2.8. Video annotation	16
2.9. Dataset summary	17
2.10. Data analysis: Logistic regression analysis	18
2.10.1. ROC curve	19
2.11. Data analysis: T-test	20

3.	RESULTS	21
3.1.	Data analysis: Logistic regression analysis	21
3.1.1.	Univariate logistic regression	21
3.1.2.	Multivariate logistic regression	25
3.2.	Data analysis: T-test	26
3.2.1.	Peak steering angle acceleration	27
3.2.2.	SD steering angle acceleration	28
3.2.3.	Peak brake pressure	29
3.2.4.	Mean absolute relative velocity	30
3.2.5.	ADAS warnings	32
4.	DISCUSSION	33
4.1.	Logistic regression analysis	33
4.1.1.	Univariate logistic analysis	33
4.1.2.	Multivariate logistic analysis	34
4.2.	T-test	34
4.3.	Study limitations	34
4.4.	Conclusion	35
4.5.	Future work	36
	REFERENCES	37
	APPENDIX A: (INDEPENDENT VARIABLES)	40
	APPENDIX B: (MATLAB CODE)	42
	APPENDIX C :(RESULTS)	47

Preface

This thesis work was carried out at SAFER, Vehicle and Traffic Safety centre, Chalmers. Working in SAFER was an incredible learning experience. I am grateful for the opportunity to be a part of this organization and wish to thank everyone that makes SAFER possible.

I wish to thank my supervisors Emma Tivesten, Volvo Car Corporation and Jonas Bärghman, Chalmers for their guidance and patience. I would also like to thank my examiner Marco Dozza, Chalmers for his support. Working with them has exposed me to true professionals and great people and I have come away greatly enriched from this experience. Many thanks to Volvo Car Corporation for allowing me access to data from its vehicles.

Not the least I would like to thank my colleagues at SAFER and my family for their uncompromising support through the years of my studies. It has been a wonderful experience growing with everyone.

Göteborg November 2011

Andre Fernandez

1. Introduction

1.1. Background

The second half of the 21st century has seen much progress in the field of automobile safety. Still, around 1.2 million people die on the road every year in traffic accidents with as many as 500 million more being injured (W.H.O., 2009). Rear-end collisions occur in car following situations when a following vehicle fails to maintain a safe distance and collides with the rear of the lead vehicle. Accidents in car following situations account for approximately 30% of all automobile crashes that occur in the United States every year. Further, research has established rear-end collisions as one of the major types of automobile accidents in the world (NHTSA, 2009). A leading cause of rear-end collisions is driver inattention due to a secondary task in the following vehicle. A secondary task is defined as a driver task that distracts the driver from the driving task such as phone use (NHTSA, 2009). Driver inattention was a contributing factor in 93% of all rear-end collisions in the 100 Car study with over 30% of all crashes and over 25% of all near crashes being caused solely by secondary-task-induced inattention (Klauer, 2006).

The effect of secondary tasks on driver performance has been a hot topic in recent years. Numerous studies have been conducted by both private and governmental organisations, seeking to better understand the effects of secondary tasks on traffic safety. According to the NHTSA, 5,870 people were killed in the United States during 2008 alone, with some form of distraction being a contributing factor while, approximately 515,000 were reported as injured (NHTSA, 2009).

Naturalistic driving studies (NDS's) such as the 100 car study (Dingus, 2006) and SHRP2¹ collected and in the case of SHRP2, are still collecting driving data from instrumented vehicles driven by subjects under naturalistic (quasi-experimental) conditions. NDS's are an important tool in road safety research, aiding the study of human factors, accident causation and crash avoidance. Advanced driver assistance systems (ADAS) such as adaptive cruise control and lane departure warning are systems that aid the driver in driving safer and more efficiently. Field operational tests such as SeMiFOT (SeMiFOT, 2008) and euroFOT (EuroFOT, 2010) are NDS's which, in addition to driving data, also collect driving data from vehicles equipped with ADAS's and allow the impact of these systems on driving to be studied. Driving data used in this study was collected from company cars driven by employees of Volvo Car Corporation during the euroFOT project.

¹ Strategic Highway Research Program 2, NDS which will study highway crashes and congestion. Currently ongoing and scheduled to run until March 2015.

1.

1.1.

1.2.

1.3.

Time gap between two vehicles in a car following situation is referred to as headway time. Previous studies have shown that headway time is influenced by secondary task distraction (Dey, 2007). Engaging in secondary task performance in certain situations poses a higher level of risk than others (McDonald, et al., 1997). Car following is one of these situations, as inattention while following another vehicle may lead to a rear-end collision if the lead vehicle has to brake unexpectedly. A better understanding of headway time and secondary task distraction in following situations could aid the development of future active safety systems.

An important step in the analysis of naturalistic driving data is finding valid data from the driving situation being studied, in the case of this thesis - car following situations. Drives through lightly trafficked road segments display a variety of headways as most drivers choose to switch lanes to a free lane if possible (McDonald, et al., 2007). This means that while instances where a driver appears to follow another vehicle may exist in a trip, several of these do not represent true car following but transient segments (lane changes, intermittent radar contacts etc.). Dey et al. studied headway behaviour and found when drives on lightly trafficked roads are considered, a range of headways are noted as drivers switch lanes to maintain a desired speed. On heavily trafficked roads however, switching between lanes is not possible and drivers are constrained to a following a vehicle (Dey, 2007). This situation is an example of a steady state car following situation and represents true car following.

Data extracted from this steady state represents true car following. Given appropriate data extraction criterion, the effect of the factors that influence headway time in car following situations can be studied without the influence of other factors such as the effects of lane changes etc. Since drivers in steady state car following situations are forced to adapt their headway to the constraining factors (the leading vehicle) this should make headway a good indicator of the driver's attention (Dey, 2007).

NDS's have shown that for several drivers, trips over a few road segments (see Figure 1) represent most of the total distance driven (LeBlanc, 2006). This thesis focus on driving data from such frequently traversed road segments. That is, segments of road along the home-work-home daily commute. The method proposed and implemented disregards data from non-steady state following situations.

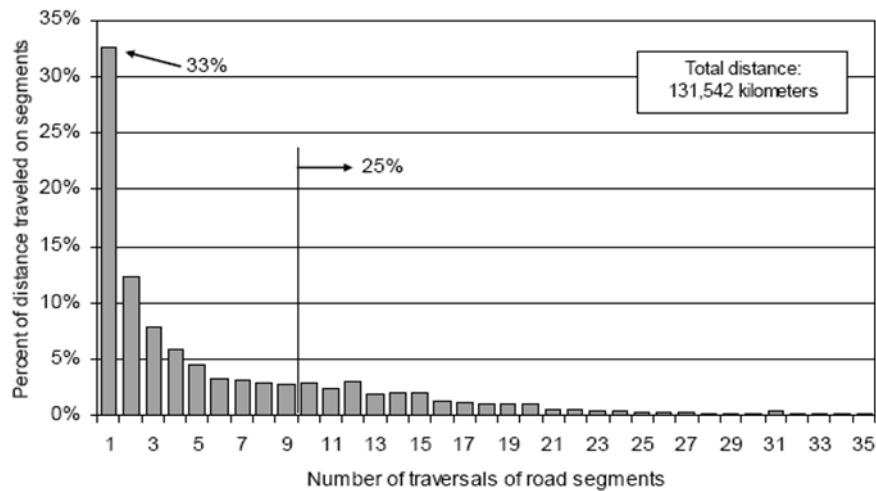


Figure 1: Percentage of distance travelled per traversal of road segment (RDCW FOT Methodology and results, 2006)

Previous studies have shown that secondary tasks have a significant effect on variables such as lane position and steering wheel angle. It was therefore expected that measures of these variables would play an important role in the analysis.

1.2. Literature review

1.2.1. Car following and headway time

The lead vehicle in a car following situation is defined as the vehicle being followed by another vehicle. This study focused on the following vehicle in this situation which is here on after called the subject vehicle. Headway time or time gap in this study is defined as the time interval between the front bumper of the subject vehicle and the rear bumper of a lead vehicle measured in seconds.

$$\text{Headway time(seconds)} = \frac{\text{Distance between lead and following vehicles(metres)}}{\text{Speed of following vehicle(metres/second)}} \quad (1)$$

The term headway can be used both to describe the gap between a lead vehicle and a follower vehicle in terms of both distance² and time³. Headway time has been described as a fundamental building block of traffic flow and indicators of traffic safety (Dey, 2007). Larger headway times have been thought to provide larger margins of safety (Yacov, et al., 2002). Vogel et al. found that small headway times indicate potentially dangerous situations (Vogel, 2001). Several national road agencies such as the Swedish national road administration recommend maintaining a headway time of at least 3 seconds (Vogel, 2001).

Headway time has been extensively studied in the past. Studies by Schuhl, Khasnabis and Dawson are among the more well-known researchers in this area. These studies used statistical methods to describe and model headway time (Schuhl, 1955; Khasnabis, 1980; Dawson, 1968).

² Headway distance

³ Headway time

Headway time in a car following situation is an important factor in the understanding of rear-end collisions. The maintenance of a safe headway time is a primary concern of drivers in car following situations (Vogel, 2001; Yacov, o.a., 2002). Headway time in a car following situation is constantly monitored by the driver so that any sudden deceleration of the lead vehicle can be handled safely by braking one's own vehicle within the available braking distance between the two vehicles thus the term 'safe braking distance'. Headway time varies considerably between individuals, is affected strongly by driver inattention and particularly by inattention due to secondary tasks (McDonald, et al., 1997; McDonald, et al., 2007; Yacov, et al., 2002). Research exists to support the fact that headway time indicates car-following, free-driving or partially constrained driving. Karjala et al. found that car following interactions cease above headway times of six seconds. (Karjala, et al., 2010). Bennet et al. found that headway times of up to 2.5 seconds describe pure car following behaviour. Headway times between 2.5 and 9 seconds were found to describe partially constrained driving (a mix between free flow and car following) with headways above 9 seconds describing free flowing driving (Dunn, et al., 1994). McDonald et al. studied car following using an instrumented vehicle in an experimental setup. It was found that day to day variations in headway time were greater than variations between the drivers (McDonald, et al., 1997).

Headway time is proposed as an indicator of car following behaviour. Although headway time has been studied in the past, few studies exist that make use of naturalistic driving data with most studies reviewed making use of either simulated data or data from closed test track experiments. No study has been found during the literature review of this thesis that models the effect of secondary tasks and other parameters on headway time in car following situations. A need for more work in this area presents itself due to its potential application in the design of future ADAS's and its role in the understanding of driver distraction and human factors.

1.2.2. Secondary tasks

Previous research has shown that secondary tasks have an effect on driving performance (Sayer, et al., 2005; NHTSA, 2009; Ranney, 2008; Dingus, 2006). In a review of the 100 Car study, Vicki et al. found that secondary task performance was the largest source of driver distraction in the study (Neale, et al., 2002). An NHTSA review of the 100 Car study found that secondary task distraction was a contributing factor in 22% of all crash and near crash situations (NHTSA, 2009; Dingus, 2006). During the same study 93% of all rear-end collisions (13 out of 14 collisions) and 68% of all near crashes involving some form of driver inattention (Neale, et al., 2002).

Klauer et al. found that engaging in a visually demanding or complex task while driving raises the crash risk by three times (Klauer, 2006). The same study suggests that the increased risk is partly due to the driver having to glance away from the road for periods longer than 2 seconds. The results from these studies suggest that in vehicle interaction with passengers, increased usage of handheld devices and other forms of in-vehicle distraction may stretch a driver's visual and cognitive resources to the point where a potentially dangerous situation may easily cause an accident.

Secondary tasks most observed during NDS's are mobile telephone/ PDA use, conversation with passengers, eating and grooming (Neale, et al., 2002; NHTSA,

2009; Sayer, et al., 2005). Conversation with passengers and mobile telephone conversations are the most often cited causes of driving performance degradation (Horrey, 2004; Neale, et al., 2002; Ranney, 2008).

The effect of mobile telephones and handheld PDA devices on driver distraction has become an issue in recent years. Vicki et al. found that phone or PDA use was a leading contributor to near-crash and crash relevant events in the 100 Car study, however only 8.7% of all crashes occurred while the driver was involved in a phone conversation suggesting that drivers take precautionary action while on the phone such as increasing headway time (Neale, et al., 2002).

Richardson et al. in an experimental study on the effects of conversational demand on driver distraction found that conversation significantly affected lateral control of the vehicle (Richardson, 2007). Visual-manual tasks (e-mails, SMS etc.) and speaking on the phone represent different levels of cognitive demand. Studies have shown that visual tasks are more demanding than speaking on the phone, resulting in greater lane keeping variance and reduced speed (Engström, o.a., 2005).

In a meta-analysis of existing phone driving studies, Horrey et al. found that phone use affected reaction time to critical events far more than tracking tasks such as lane keeping (Horrey, 2004). Horrey et al. further suggests that the two tasks demanded different resources and are therefore impacted differently by phone conversations.

1.3. Naturalistic driving data, field operational tests and EuroFOT

Naturalistic driving data is obtained from test vehicles equipped with data acquisition systems and sensors (EuroFOT, 2009). These vehicles are typically driven by test subjects with directions to be used as their own vehicles with a few restrictions such as being restricted to drive within certain geographic boundaries or certain routes. The subject operates the vehicle over an extended period of time and due to this comes to pay little attention to the data capture equipment (LeBlanc, 2006; Dingus, 2006). Data is typically stored in the vehicle and is transferred periodically to a central collection system for storage and analysis. Some data comes from interviews and questionnaires.

The data used in this study comes from Volvo Car Corporation's test vehicles in the euroFOT project. euroFOT is a European Commission sponsored effort; with 28 partners whose main goals are to test modern ADAS's on drivers under naturalistic driving conditions and assess the impact of these systems on safety, efficiency, mobility and the environment.

The data available from the euroFOT driving study includes

- Information from the vehicles internal CAN bus(example: steering wheel angle)
- Video data from in-vehicle cameras. 5 channels of video data are available.
 - Driver camera
 - Road camera

- Rearward facing camera
- Foot camera
- Eye Tracker camera
- Data from GPS, accelerometers etc.

Driving data was saved to an on-board medium at a frequency of 10 Hz. Data was then downloaded, post processed and made accessible for research within the contractual boundaries of the euroFOT project. Other NDS's and field operational tests such as the 100 Car study and the RDCW FOT⁴ also share a similar methodology (LeBlanc, 2006; Dingus, 2006).

The ADAS's tested in the euroFOT included:

- Forward collision warning systems
- Adaptive cruise control
- Lane departure warning systems
- Impairment warning systems
- Blind spot information systems

Data security in NDS's is a delicate and important issue. Information such as the coordinates of the test subjects residences and video data of the test subjects are examples of potentially sensitive information, as well as commercially sensitive data from the vehicle manufacturer where e.g. warning strategies or sensor performance can be reverse engineered. Data is thus treated with the utmost regard for the privacy of the test drivers and with regard to the commercial aspect with strict protocols governing the access, use and extraction of data (Bärgman, o.a., 2011; FESTA, 2008).

1.4. Aim

This research aims to study secondary task distraction in car following situations. A method will be developed where steady state car following situations will be defined and these segments identified from the data. This data will then be extracted and used to build statistical models of secondary task performance. It is hoped that an insight will be gained into the effects of secondary tasks on driving performance during steady state car following. Headway time and other variables will be used as measures of driver performance during these steady state following situations.

⁴ Road Departure Crash Warning System FOT

2. Method

In the course of this study, data segments from the euroFOT database were extracted, annotated for secondary task performance and analysed. Logistic regression was used to study the effects of secondary tasks on car following. Data from each trip made by drivers in the euroFOT was available as individual files in the euroFOT database. All data processing was performed in the MATLAB software environment (Mathworks, 2011). A naturalistic driving data analysis tool, FOTware (FOTware, 2010) was used to analyse data.

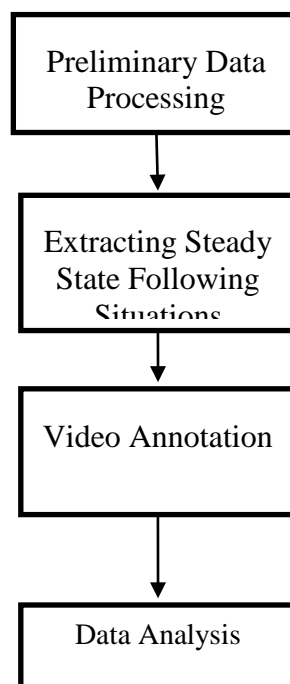


Figure 2: Methodology: Overview

Figure 2 illustrates the methodology of this study. After the drivers were selected, all valid trips from the database made by those drivers were saved to local data files to simplify further processing and analysis. Driving data from selected road segments was extracted and filtered into data segments representing steady state car following situations. Video clips of the road and driver cameras from the steady state following segments were then made. These clips were annotated for secondary task performance and statistical measures of the data were calculated. Logistic regression was then used to study the effect of secondary task performance on car following.

This thesis work was conducted at SAFER, Vehicle and Traffic Safety centre, Chalmers. This thesis was conducted while data for the euroFOT was still being collected in the field. This meant that a limited set of data was available at SAFER for the analysis part of this thesis.

2.1. Road segments

The test vehicles considered in this study were full sized Volvo sedans and station wagons. The subject drivers were all VCC employees with a mean age of 35 years. Figure 3 shows a typical drive for the subject drivers. As noted in the previous chapter most of a driver's mileage is made over relatively few road segments. In urban driving environments these heavily trafficked road segments are typically main arterial roads with the appropriate Swedish term being 'Motortrafikled' (Encyklopedin, 2011). This type of road normally has two lanes in each direction, with a steel divider. Data from selected main arterial road segments was extracted for this study. The average length of the road segments in the study was approximately 3 kilometres.

Radius of curvature of a point on a road is defined as the radius of a circle that best fits the curvature of the road at that point. A perfectly straight road has an infinite radius of curvature while sharp curves are considered to be between 100 to 400 metres in radius. Note that several factors including superelevation⁵, road surface friction etc. influences the sharpness of a curve. For example a curve with a relatively small radius of curvature may be considered less sharp than a curve with a larger radius if the smaller curve has a higher superelevation angle than the larger. However radius of curvature alone was used to define the curvature of road segments in this study. Past studies consider roads with radii greater than 500 meters to be straight (ISO 17361: 2007, (Visvikis, et al., 2008). Roads Curve radius has been shown to have significant effects on driving (Rune Elvik, 2009). Studies have shown that accident rates are significantly higher on curves than on straight road sections (Othman, 2008). Elvik et al. noted a slight increase in the accident rate with decreasing curve radii of between 1000 to 400 metres. A sharp increase in accidents was seen on curves less than 300 metres in radius (Rune Elvik, 2009). In order to negate the effect of curves on the

⁵ The banking of a road to counter centripetal forces in a vehicle on a curved road section. Values range from 10 degrees(full super-elevation) to -2 degrees(normal super-elevation)

variables in the study it was decided to focus on relatively straight road segments. Data from curves less than 300 metres in radius was thus excluded from the analysis.

Radius of curvature of the road was found from the equation given below (Carlson, o.a., 2006).

$$R = ((57.3 * L) / \Delta) \quad (2)$$

Where

R = Radius of curvature

L = Roadway Curve Length

Δ = Change in vehicle heading

2.2. Drivers

Drivers were selected based on several criteria with the highest priority being that the driver was associated with large volumes of time history data from the road segments of interest. GPS traces (Figure 4) were used to infer the routes most commonly driven by the subject driver. Drivers typically used their vehicles for commuting between their place of work and residences during the week and tended to favour a particular route or a few routes. Usage for recreational purposes was less frequent. Therefore by extracting data from only heavily trafficked road segments a preference was shown to data from commuting between home and the driver's work spot.

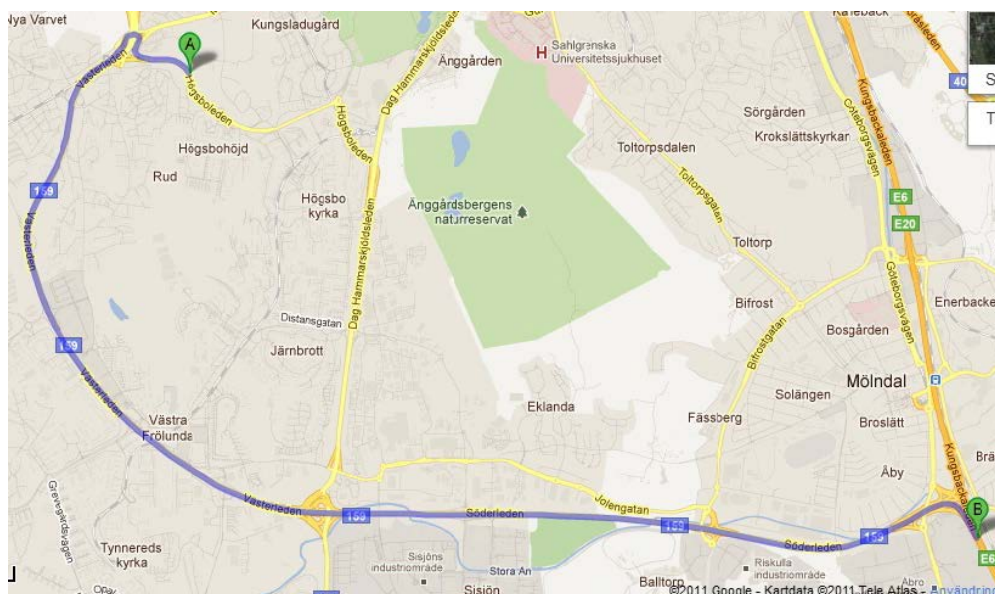


Figure 3: Example of a typical commute (Source: Google Maps)

Figure 3 illustrates a typical daily commute of a driver in this study. The driver starts at a semi- suburban residential district, drives most of the distance on a motortrafikled and arrives at the commercial or industrial area where he or she is employed.

Figure 4 shows a GPS trace of the driving history of a typical driver. Regions of greater intensity allowed a rudimentary estimation of the trip density through those segments and helped in the selection of work commute road segments. A count of trips through these road segments was made and the final road segments were selected.



Figure 4: GPS Trace of Driver

2.3. Independent variables

Independent variables in this study are time varying quantities which are either continuous or categorical in nature. Independent variables hypothesized to have an effect on the aspects of car following in this study were selected. The most prominent of these were used as predictors in the statistical analysis to study the effect of secondary tasks on headway time.

Data such as CAN signals, Video data etc. were available from the euroFOT database. Variables were selected for study on the basis of their hypothesized influence on car following. Continuous independent variables were mostly physical quantities such as vehicle dynamics information while categorical variables were indicators such as wiper flags, daytime flags etc. Complete descriptions of variables used in this thesis can be seen in Appendix A.

Information on secondary tasks was categorical, with null values signifying no instances of a secondary task in a data segment and a value of one signifying a

secondary task. This information was obtained by annotating video clips from the data segments.

FOTware is a tool for the visualization and analysis of naturalistic driving data developed at SAFER, FOTware was used to analyse the variables. The variation in each variable in relation to other variables can be visualized while simultaneously watching synchronized video feeds from the test vehicle cameras. Figure 5 shows a typical layout with the signal viewer on the left and video from the road and driver cameras on the right.

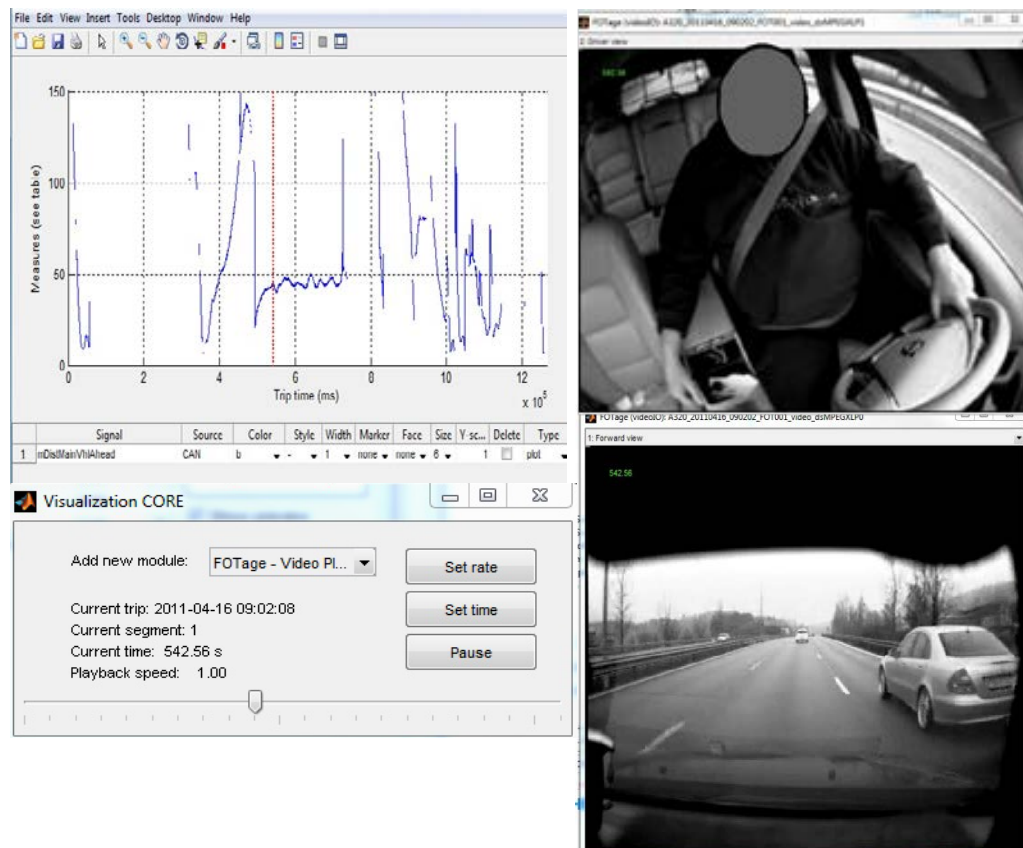


Figure 5: FOTware

2.3.1. Secondary task variables

Data on secondary tasks was not available from the euroFOT database and had to be obtained by the manual annotation of videos (see section 2.8). Previous research has shown that the leading sources of secondary task distraction are mobile phones, conversations with passengers, eating and grooming (Sayer, o.a., 2005; Dingus, 2006). These four tasks were chosen and their effect on car following was investigated. Instances of secondary tasks were identified by annotating video from the driver facing camera. Audio data was not available for use in the analysis. The Coding variables handbook developed at SAFER was used as a basis for the definitions

of the secondary tasks, brief descriptions of which are given below. For more detailed descriptions please refer Appendix A.

2.3.1.1. Mobile telephone use

Phone use among drivers can be categorised as either hand held or hand free usage. Hand held usage includes conversations while holding the phone to the ear, text messaging, using a smartphone to check emails etc. While studies suggest that the different modes of phone use among drivers demand varying amounts of the driver's cognition this study placed all types of phone use under a single category.

2.3.1.2. Conversations and passenger related activity

Conversation with passengers was defined as instances where the driver was seen to actively participate in a conversation with their fellow passengers. It was not possible to annotate instances where the driver participated in a conversation as a listener although this type of conversation also places demands on the driver's mental resources. Instances where the drivers was seen to utter a single word or move their mouth's in a manner suggesting a single word were not considered as constituting a conversation.

2.3.1.3. Eating

Eating was defined as instances where the driver was observed eating food from a utensil or paper bag with their own hands or with the aid of a fork or spoon etc. Chewing gum use identified from extended periods of repetitive jaw movement was not considered eating.

2.3.1.4. Grooming

Grooming was defined as instances of the driver diverting attention away from the driving task to concentrate on any aspect of their personal appearance. This included the combing of hair, dental hygiene, makeup application etc.

2.4. Data processing

Data extraction is a crucial part of the analysis of naturalistic driving data. After a general idea of the types of data and statistical methods that would be used in the analysis was formed, data was extracted from the euroFOT database and compiled into driver specific data files. These files were further processed to extract car following data. Data was extracted and processed in two steps:

- Preliminary data processing.
- Extraction of steady state car following data.

2.5. Preliminary data processing

The euroFOT data is stored at SAFER within a closed computer network. Data on this network is available in the form of Matlab (Mathworks, 2011) compatible data files and as an Oracle based database. This study makes use of the data files. Each data file

represents a single trip made by a driver. A trip is defined as the time from when the vehicle ignition is turned on and when the vehicle ignition is turned off. These trip files are imported into Matlab and filtered to extract the required information.

All valid data for the selected driver was extracted from the euroFOT database and saved for further processing. This allowed for several road segments to be evaluated for car following and secondary task segments before the final road segments were chosen. From a GPS trace (Figure 6) it is seen that a significant amount of driving data from the road segment highlighted in red was available. The driving data from this road segment was evaluated for data integrity (missing variables, missing video data etc.). If data quality was found to be acceptable, the road segment would be selected for further analysis and data from the segment (Figure 7) was then saved separately.

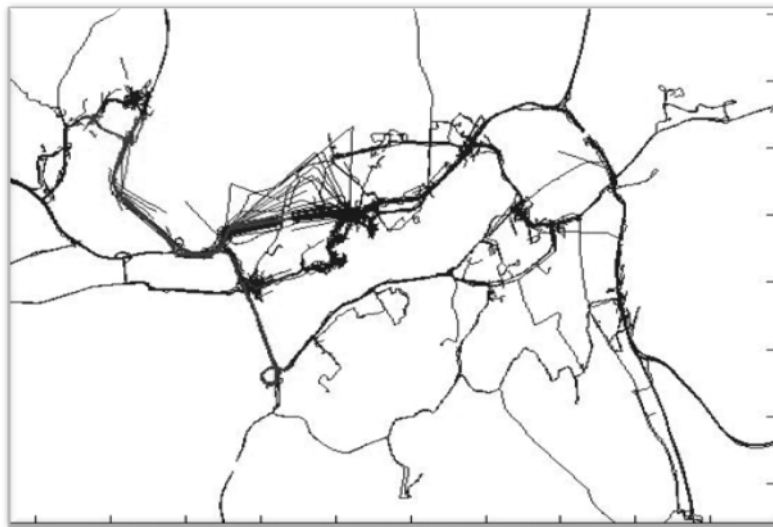


Figure 6 : GPS trace: Areas of greater intensity indicate high trip density

2.6. Extraction of steady state car following data

Data from the selected road segment was then processed to extract car following data. Figure 7 shows car following data from a road segment. This section presents the definition of steady state car following and the extraction of data from these segments. After data from car following situations was extracted, statistical measures of independent variables were calculated and saved into a spread sheet.

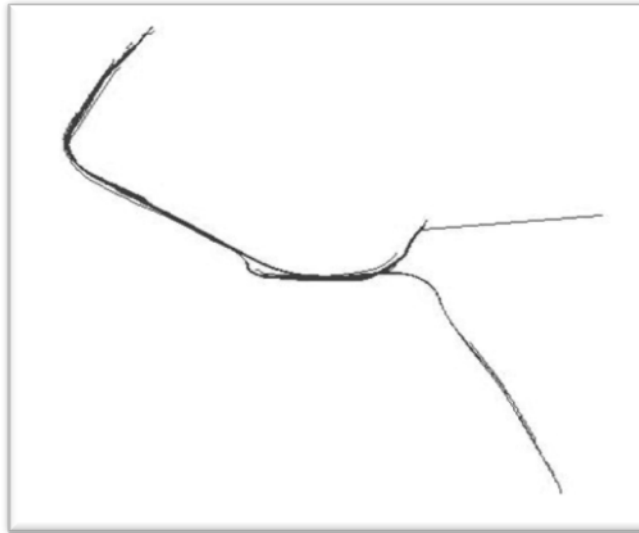


Figure 7: Steady state car following segments

As introduced in Section 1.3, steady state car following defines a driving situation where the following behaviour exhibited by the driver of the subject vehicle can be said to be defined by the behaviour of the leading vehicle. The factors used in the definition of the steady state are described below.

2.6.1. ACC

Adaptive cruise control maintains a pre-set minimum distance or headway time from a leading vehicle. This removes the need for a longitudinal control input from the driver and makes these segments irrelevant for the purpose of this study. Data segments where the ACC is activated were therefore excluded.

2.6.2. Speed of subject vehicle

Vehicle speed was used to exclude data from low speed manoeuvring/ traffic gridlock situations. A minimum vehicle speed of 20 kmph was used as a threshold speed and all data falling below this speed was excluded.

2.6.3. Lane changes and lane change residuals

Lane change manoeuvres involve the driver steering the vehicle into another lane. This could invalidate the segment by combining data from the lead vehicle in the first segment with data from the lead vehicles in the second segment. It was necessary to eliminate lane change manoeuvres. Lane changes were detected by two methods. Spikes in the radar range signify events where the radar range changes suddenly, as it would when the driver changes lanes and starts to follow a lead vehicle driving at a different speed than the first lead vehicle. This approach does not detect situations where, after a lane change the driver begins to follow a lead vehicle driving at approximately the same speed as the first lead vehicle as no spike would be observed in this case. The cars turning radius was used to detect and filter these situations. Lane change events inferred from the vehicles yaw rate were available from the database but were not used to identify lane change events as they did not identify all lane change events.

Previous studies show that most lane changes take approximately 5 seconds to complete (Salvucci, o.a., 2002). Changes in driver behaviour have been noted in the period before the driver initiates a lane change. This phase was termed the lane change preparatory phase. The period from the initiation of the lane change preparatory phase to the conclusion of the lane change does not represent steady state car following and was filtered.

2.6.4. Lead vehicle cut –ins/cut – outs

Cut- ins are defined as when a third vehicle from another lane steers into the lane of the subject vehicle and places itself between the subject vehicle and the lead vehicle. A cut out is defined as when a lead vehicle steers out of the subject vehicle lane and a new radar contact is immediately picked up by the subject vehicle. Spikes in the difference between successive radar range values were used to identify cut-ins and cut-outs.

2.6.5. Range to lead vehicle

The range to a lead vehicle is highly correlated with headway time. From driving studies it is known that following situations are defined by headway times of 6 seconds with headways of above 9 seconds coming from free driving situations (Dunn, et al., 1994). From analysis of the data it was found that a range of 100 metres or less to the lead vehicle correlates to a headway of around 6 seconds. This range was thus used as a threshold and data from ranges above 100 metres was excluded.

2.6.6. Segment length

A minimum segment length was defined and used as an exclusion criterion. Data segments were to be a minimum length of 100 metres (travelled on road) to be considered steady state segments. This was to filter segments where steady state following lasts for short durations (typically of 1 – 3 seconds in duration). These segments are hypothesised to be transient in nature and not representative of true steady state following. A good example for a situation of this type is one where a driver wishes to steer into the right hand lane and momentarily comes to within 100 metres of a vehicle in the left lane.

2.7. Assumption of independence

Time series data from NDS's tends to exhibit a degree of autocorrelation. That is, datapoints from the same period of time are related to one other. This violates the assumption of independent observations in statistical methods such as linear regression and is termed autocorrelation. Thus in this study, when statistical measures from data segments in the same trips were used to study car following autocorrelation between concurrent trip segments may bias the findings. This can be exemplified by taking two following segments from the same trip, each occurring within 30 metres of

the other. Variables from these segments would tend to be very similar thus biasing any models fit to this data.

Autocorrelation in this study was not explicitly calculated but was minimized in two ways. Firstly, data from the same trip but from different trip segments were assumed to be independent if the lead vehicle in each following trip segment was different. This assumption was based on findings from previous research that indicates different lead vehicles impose different constraints on the following driver, forcing the following driver to alter following behaviour when the lead vehicle is changed. Mulder et al. and Mc. Donald et al. take car following to be a compensatory action where the following driver seeks to maintain a constant headway time and keep relative velocity between the vehicles as close to zero as possible (Mulder, o.a., 2006; McDonald, o.a., 1997). The velocity profile of the lead vehicle therefore has a strong effect on the following driver. The size and type of the lead vehicle is also a factor in car following. Drivers in a following situation tend to maintain shorter headways if the road ahead was not visible past the leading vehicle (Sayer, et al., 2009; McDonald, et al., 2007). The same studies also found that drivers tended to maintain shorter headway times to commercial vehicles hypothesizing that the degree of trust shown to professional drivers was greater than the trust in private drivers.

Secondly, autocorrelation between segments from the same trip and with the same lead vehicle arise from situations where the driver intermittently approaches and backs away from the lead vehicle. Mc. Donald et al. used a separation time of 5 seconds to avoid excessive autocorrelation between readings (McDonald, et al., 1997). In this study, autocorrelation from these segments was handled by introducing a minimum separation criterion of 8 seconds. At average motorway speeds this corresponds approximately to a mean separation of 150 metres between segments. Consecutive trip segments found to lie closer to each other than 8 seconds were combined into a single segment⁶.

2.8. Video annotation

This step involved the annotation of video clips from car following segments (see section 2.6) for instances of secondary tasks. Annotation using FOTware was found to be time consuming. It was found to be more efficient to create video clips from the original video files of the whole trip and watch the clips with a media player. Video files were watched and annotated for secondary tasks. Instances of secondary tasks were saved as binary variables and tabulated using Microsoft Excel. Segments that were found to have missing or corrupted video (over exposure⁷ etc.) were excluded. Several drivers were excluded from the study for these reasons.

The video Annotation codebook (Viström, 2011) developed at SAFER was used as a starting point in developing guidelines for secondary task annotation. Duration of task performance and the duration of glances away from the road were the primary

⁶ Please refer section 3.2.1 for more details.

⁷ Excessive light.

factors considered in the rating of trip segments as secondary task segments. To be considered a secondary task instance the driver should have been observed performing the task for more than two seconds. Although the relative duration of the secondary task to the trip segment was not found to be an issue in an overwhelming majority of the cases and therefore was not considered, a few instances such as long trip segments where the secondary task lasted for a small fraction of the total trip duration were excluded.

In order to qualify as a secondary task instance, an increase in the frequency of glances away from the road must also have been noticed. Previous research has found that an increased frequency of eye glances away from the roadway has been found to be common in secondary task instances (Klauer, 2006). Phone usage for messaging or e-mails in particular was found to result in a greatly increased eye glance frequency with frequencies of 1 Hz being observed in some instances.

An important point to note is that annotating driver behaviour is a subjective matter that requires video data to be interpreted. Individual drivers display unique driving styles, for example a certain individual's baseline eye glance frequency might be the same as that shown by other drivers during secondary task instances. It was therefore important to for the annotator to get familiar with the different drivers normal behaviour in order to understand if secondary task performance had any effect on their driving. This was done by viewing videos from baseline driving segments to understand driver specific traits such as eye glance duration and frequency of glances away from the roadway. Video annotation in this study was carried out by a single annotator – the author of this thesis.

2.9. Dataset summary

The results discussed in this report will focus on a single driver. Two versions of the dataset were used in the analysis. The first was the entire car following dataset (see section 2.6). This dataset potentially contained data from both partially and fully constrained car following segments. The second version of the dataset seeks to exclude partially constrained segments using the headway time⁸ and relative velocity⁹ as filter criteria. Segments with headway times greater than 2.5 seconds and relative velocities of greater than 2 km/h were excluded.

As shown in Table 2 the unfiltered dataset used in the study contained 165 observations from 64 trips. 54 segments were combined to limit autocorrelation between trip segments (see section 2.7) and an additional 76 were removed when constraints based on mean headway time and mean absolute relative velocity were imposed (Table 1: Row 2). Secondary task instances are listed with the number of

⁸ Studies have shown headway times less than 2.5 seconds describe fully constrained 'true' car following situations (Dunn, o.a., 1994).

⁹ Drivers in fully constrained car following maintain the relative velocity between lead and subject vehicle as close to zero as possible, typically less than ± 3 km/h (McDonald, o.a., 1997).

trips from which the observations were drawn. No instances of grooming or eating were observed.

Table 1: Dataset Summary

	Total following segments	Total trips	Phone Use Instances	Conversation	Grooming	Eating	Number of segments combined
Unfiltered dataset	165	64	40 in 20 trips	5 in 3 trips	1	2 in 1 trip	54
Headway < 2.5 seconds & Relative velocity < 2 km/h	89	50	19 in 15 trips	4 in 3 trips	0	0	

Table 2 shows secondary task performance expressed in terms of total trip percentage.

Table 2: Secondary Task Performance

Phone Use (% of trips)	Conversation (%)	Eating (%)	Grooming (%)
21	4.5	0	0

2.10. Data analysis: Logistic regression analysis

Logistic regression models a dichotomous (binary) variable using one or more independent variables as predictors. Logistic regression in this study was used to model secondary tasks instances using measures of independent variables as predictors.

The logistic function can be written as:

$$f(z) = \frac{1}{1+e^{-z}} \quad (3)$$

The variable z is expressed as:

$$z = \beta_0 + \beta_1 \cdot X_1 + \dots + \beta_n \cdot X_n \quad (4)$$

Where

$\beta_{0,1}$ = Regression Coefficients

X_i = Predictor(independent) variables

Univariate logistic models of secondary task occurrence were first fit using independent variable measures as predictor variables (See Appendix A for a complete listing of measures). A p value of 0.05 was used as a threshold for the Univariate model. However any measure with a p value lower than 0.25 (Hosmer, et al., 2000 p. 95) was considered significant in the variable selection step of the multivariate model. The relatively high value of p is based on research that suggests using a lower value of p in the variable selection stage often results in important variables being missed¹⁰. A drawback of a high value is that variables of questionable importance may be selected for use in the model. Phone use was first used as a predicted variable. Models were then fit to a combination of all secondary tasks¹¹.

Significant measures of variables identified during the univariate analysis were used as predictors in the multivariate model of secondary task occurrence. Interaction effects were considered in the multivariate model. The accuracy of the models were assessed using their ROC curve¹² and t test statistics (Hosmer, et al., 2000 p. 93). Figure 8 shows the logistic curve of the model using relative velocity as an independent variable. The plots indicates the calculated probability of phone use occurring in the data segment with values of 1 suggesting phone use and values of 0 suggesting baseline driving. An iterative approach was used here where each variable was individually combined with the other variables iterating through all the possible combinations.

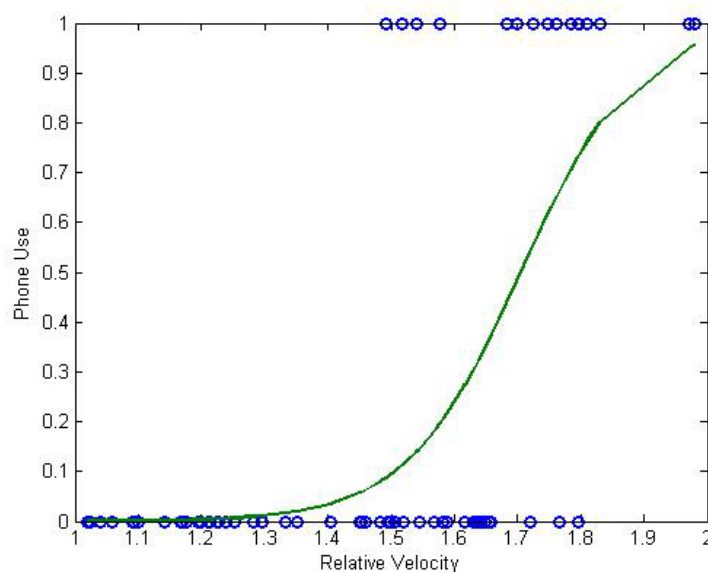


Figure 8: Logistic curve: Univariate model of phone use from relative velocity

2.10.1. ROC curve

The ROC (Receiver Operating Characteristics) curve originates from signal detection theory developed during the Second World War. ROC curves plot a systems sensitivity (true positive rate) against its false positive rate (specificity) for different cut-off points. The cut-off points in the case of this study are the threshold values of

¹⁰ See Applied Logistic Regression (Hosmer, et al., 2000), p. 95

¹¹ A variable indicating the performance of any secondary task.

¹² See Section 2.10.1

classifier scores from the logistic model. The ROC curve is thus a visualization of the trade-off between the sensitivity and specificity of the model. Figure 9 shows a general ROC curve with threshold points indicated. A good model of a dichotomous variable will have a high detection rate of both true positives and true negatives. The curve in this case would at one point lie near the upper left corner (100% sensitivity, 100% specificity) (Zweig, et al., 1993). The model can also be assessed by the area under the ROC curve (Hosmer, et al., 2000 p. 160). The area under the ROC curve can be related to the models accuracy by the values listed below (Hosmer, et al., 2000 p. 162)

Area under curve = 0.5 – No discrimination

Area under curve between 0.7 & 0.8 – Acceptable discrimination

Area under curve between 0.8 & 0.9 – Excellent discrimination

Area under curve > 0.9 – Outstanding discrimination

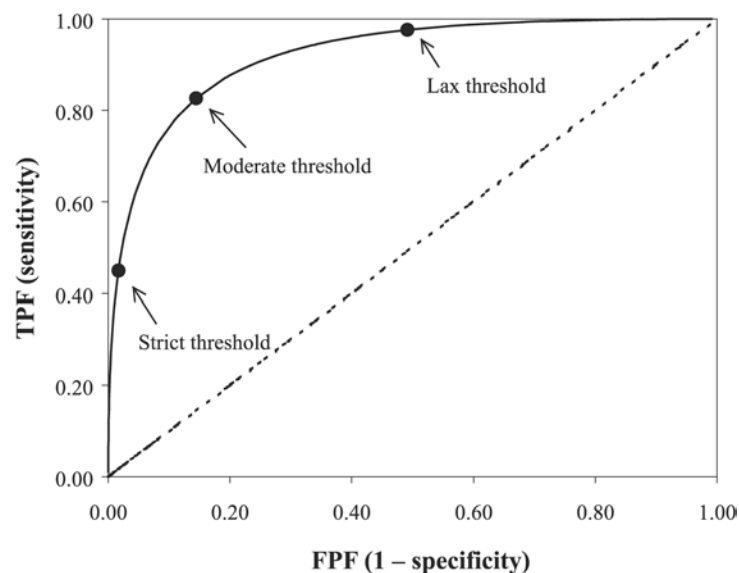


Figure 9: ROC curve(Illustration)

2.11. Data analysis: T-test

Statistical measures such as standard deviation are commonly used to study independent variables in NDS's. This study considered baseline situations to be car following situations containing no secondary task instances. Comparisons were made between measures from baseline segments and secondary task segments to infer a connection between secondary task engagement and changes in the measures. Only statistically significant variables identified from the logistic regression analysis were analysed further in this section.

Measures from the logistic regression analysis found to be significantly correlated with secondary tasks were tested against the alternative hypothesis that the means of baseline and secondary task segments are unequal. It is possible to test the significance of variates in the logistic model with the two sample T-test (Hosmer, et

al., 2000 p. 92). Independent T-tests of all significant measures from the logistic analysis were performed and baseline and secondary task segments of interesting measures were then compared. The results are described in section 3.2.

3. Results

Results from the statistical analysis are presented in this chapter. The results are presented based on the analysis of data obtained from a single driver driving over a single stretch of road.

3.1. Data analysis: Logistic regression analysis

Results from the univariate and multivariate logistic regression analysis of the filtered dataset are presented in this section. Only statistically significant results or results that came close to being significant are listed here. See Appendix C for a complete listing of results from the logistic regression analysis.

3.1.1. Univariate logistic regression

Results from the model predicting phone use are presented in Table 3. Several measures were found to be statistically significant (Peak & SD steering angle acceleration, peak brake pressure, SD longitudinal jerk & acceleration, mean & SD relative velocity). Significant results are highlighted in bold. See Appendix C for a complete listing of results. No measures reached significance in the model which was used data from the unfiltered dataset.

Table 3: Single Predictor model: Phone Usage (Filtered Dataset)

Measure	P value
Peak steering angle acceleration	0.0197
SD steering angle acceleration	0.0251

Mean steering angle velocity	0.0508
SD steering angle velocity	0.1046
Mean Headway time	0.1219
Peak brake pressure	0.0311
SD brake pressure	0.1022
SD longitudinal jerk	0.0462
Max longitudinal acceleration	0.1555
SD longitudinal acceleration	0.0173
Mean relative velocity	0.0020
SD Relative Velocity	0.0039

Results using any secondary task¹³ as a predicted variable are presented in Table 4. In the analysis of the filtered dataset only peak and standard deviation of steering angle acceleration and mean and standard deviation of relative velocity reached significance. Fewer significant measures (4 compared to 7) were noticed when comparing the results from this test (Table 4) with the previous (Table 3). No measures reached significance for the unfiltered dataset.

Table 4: Single Predictor - Any Secondary Task (Filtered Dataset)

Measure	P values
Peak Steering Angle Acceleration	0.046
SD Steering Angle Acceleration	0.028
Mean Steering Angle Velocity	0.062
SD Steering Angle Velocity	0.156
Mean Abs Relative Velocity	0.019
SD Relative Velocity	0.034
SD Longitudinal Acceleration	0.085
SD Longitudinal Jerk	0.136

¹³ Variable indicating the performance of any secondary task.

Figure 10 shows the ROC curve for Mean relative velocity (phone usage, filtered dataset). From the curve shape it was seen that the model performs well in identifying phone use events (true positives) and baseline segments (true negatives). The area under the curve (Table 5) for this model (0.89) also indicates good classification.

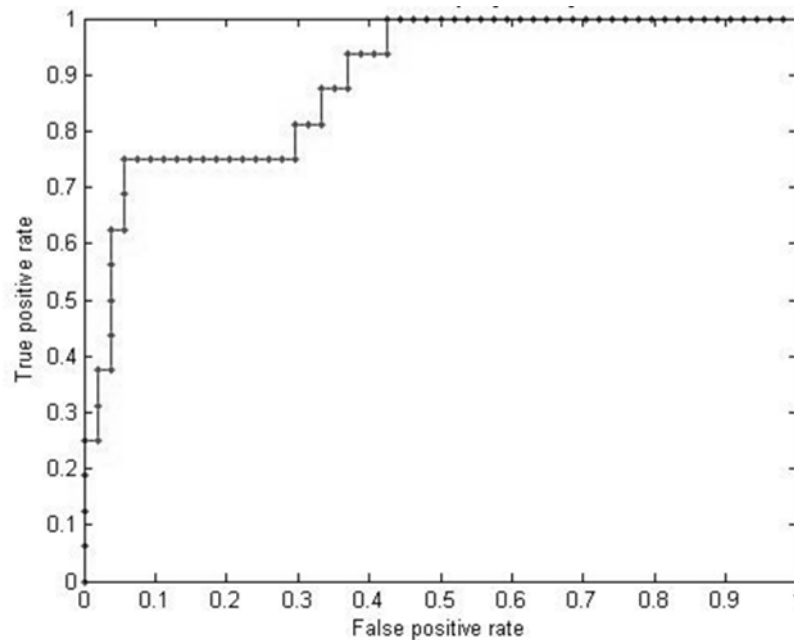


Figure 10: ROC curve(Relative velocity)

The ROC curve of mean steering angle velocity (Figure 11) indicates that in the case of the driver in question, the measure may not be as good a classifier as relative velocity. However an AUC of 0.72 indicates that mean steering angle velocity may be a fair classifier of phone usage.

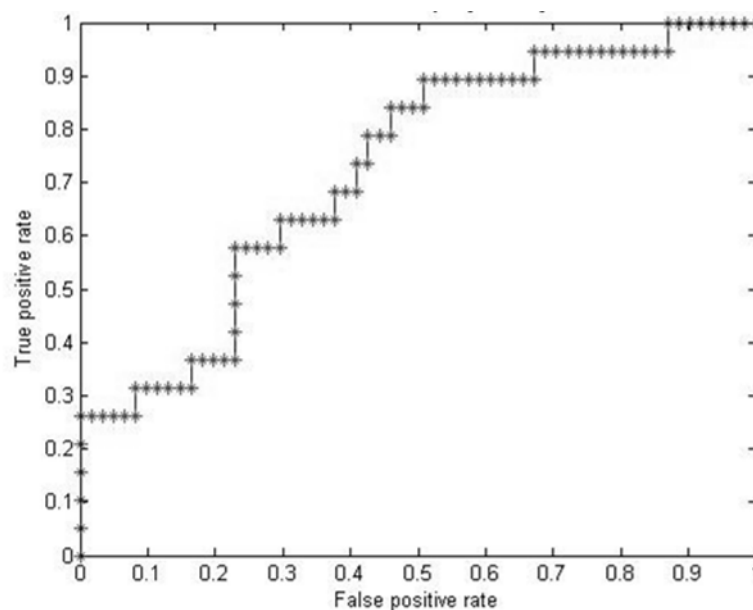


Figure 11: ROC curve(Steering Angle Velocity)

Figure 12 shows the ROC curve of peak longitudinal acceleration. Compared to the curves described previously, this curve lies much closer to the diagonal. The area under the curve in this case is 0.65 indicating a poor fit. ROC curves from other significant measures can be found in Appendix C.

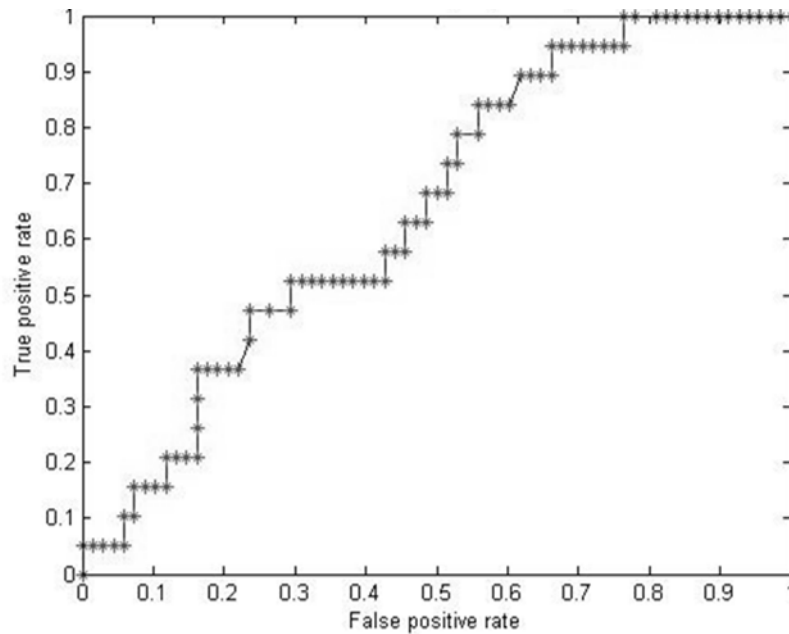


Figure 12: ROC curve(Peak Longitudinal Acceleration)

Table 5: Single predictor: Area under curve

Measure	AUC
Peak steering angle acceleration	0.71
SD steering angle acceleration	0.67
Peak brake pressure	0.81
SD longitudinal jerk	0.71
SD longitudinal acceleration	0.74
Mean relative velocity	0.89

ROC curves of statistically significant¹⁴ measures from the univariate logistic analysis yield for the most part acceptable AUC values (Table 5). The AUC values of measures that were not statistically significant were low (Table 6). No statistically

¹⁴ P value

insignificant predictor yielded an AUC value higher than 0.53. A full list of AUC values can be seen in Appendix C.

Table 6: Single Predictor: Area under curve (Insignificant Factors)

Measure	AUC
Mean Yaw Rate	0.50
Max Yaw Rate	0.51
SD Yaw Rate	0.49

3.1.2. Multivariate logistic regression

Table 8 lists results from the multivariate logistic analysis of phone use. The first model used all significant measures from the univariate analysis as predictors. This model did not consider interaction effects (Table 7: Row 1). Steering wheel angle measures were found to remain significant while the other measures did not. Selected results from the modelling of phone use with selected lateral and longitudinal measures are also seen in the table. The peak steering acceleration, peak brake pressure and longitudinal jerk terms were seen to be significant indicators of phone use. Interaction terms from all tests were not statistically significant.

Table 7: Multivariate Logistic Regression: Phone Use

Test	Significant Measures	P value
All significant measures from single predictor model, no interaction effects.	Peak steering angle acceleration	0.0212
	SD steering angle acceleration	0.0209
Peak steering angle acceleration & brake pressure with interaction effects	Peak steering angle acceleration	0.0040
	Peak brake pressure	0.0062
SD steering angle Acceleration & peak brake pressure with interaction effects	SD steering angle acceleration	0.0026
	Peak brake pressure	0.0043
Peak Steering Angle with interaction effects Acceleration & SD longitudinal jerk	Peak steering angle acceleration	0.0086
	SD longitudinal jerk	0.0156
Mean headway & SD longitudinal jerk	Mean Headway	0.1471
	SD longitudinal jerk	0.0886

3.2. Data analysis: T-test

Table 8 lists the results from two sample T test hypothesis testing of selected measures. Values of 1 indicate rejection of the null hypothesis and values of 0 indicate a failure to reject the null hypothesis at a 95% confidence limit. Continuous performance indicators such as headway and lane offset were not found to be significantly affected by phone use. However indicators of driver control input (or responses to critical events) such peak steering angle acceleration, peak brake pressure and standard deviation were significantly affected.

When data from phone use and baseline segments in the unfiltered dataset were compared no significant difference was found between baseline and phone use segments. This reflects similar results from the logistic regression analysis.

Table 8: T-test (Phone Use)

Measure	T-test			
	Unfiltered dataset	Headway < 2.5, Relative velocity < 2	Mean of Means(baseline, filtered dataset)	Mean of Means (secondary task, filtered dataset)
Mean Headway(s)	1	0	1.0671	0.8976
Peak steering angle acceleration(deg/s/s)	0	1	247	337.6
SD steering angle acceleration	0	1	38.80	48.47
Peak Brake Pressure(bar)	1	1	4.6	8
SD longitudinal jerk(m/s/s/s)	0	1	1.7	1.9
SD longitudinal acceleration(m/s/s)	0	1	0.3914	0.4762
Mean relative velocity(km/h)	0	1	1.6427	1.3513

3.2.1. Peak steering angle acceleration

Peak steering angle acceleration was shown to be a statistically significant factor in the logistic regression analysis. Standard deviation of the mean values from baseline segments was seen to be lower than the values from secondary task segments. Secondary task segments exhibit a higher mean of means. The mean of means was found by finding the mean over all values of mean peak steering angle acceleration from the segment under study.

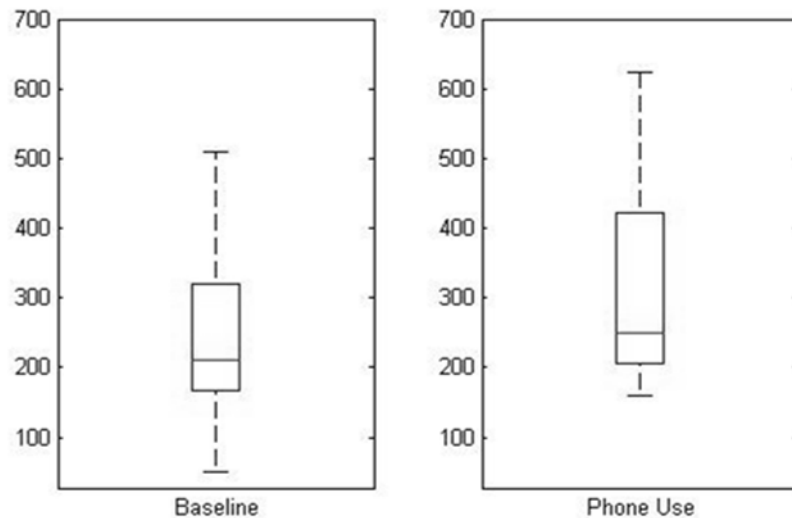


Figure 13: Peak steering angle acceleration

Table 9: Peak Steering Angle Acceleration: Phone Use

Peak Steering Angle Acceleration(m/s/s)	Mean of Means	SD of Means
Baseline Segments	247	111.4
Secondary Task	337.6	197.3

3.2.2. SD steering angle acceleration

Standard deviation of steering angle acceleration was found to be clearly statistically significant in the logistic regression analysis. The mean of means and standard deviation of baseline segments were seen to be lower than the values from secondary task segments.

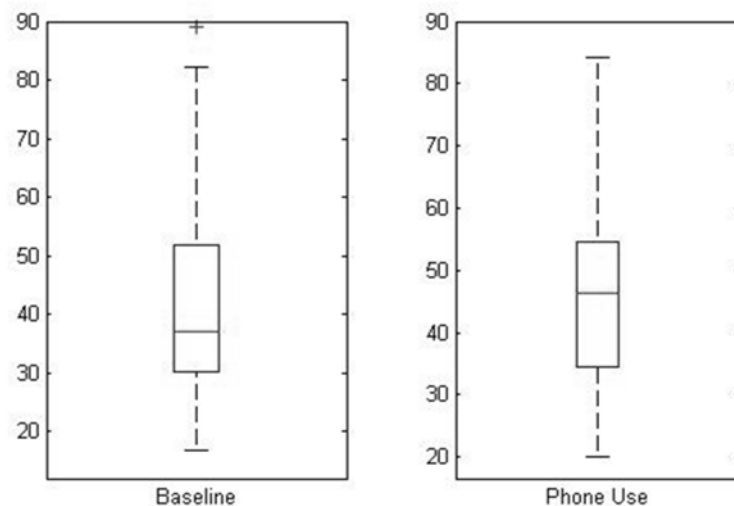


Figure 14: SD steering angle acceleration

Table 10: SD Steering Angle Acceleration: Phone Use

SD Steering Angle Acceleration	Mean of Means	SD
Baseline Segments	38.8	14.65
Secondary Task	48.4	19

3.2.3. Peak brake pressure

The mean of means of baseline segments were less than the means from secondary task segments. SD values from baseline segments were higher than secondary task segments.

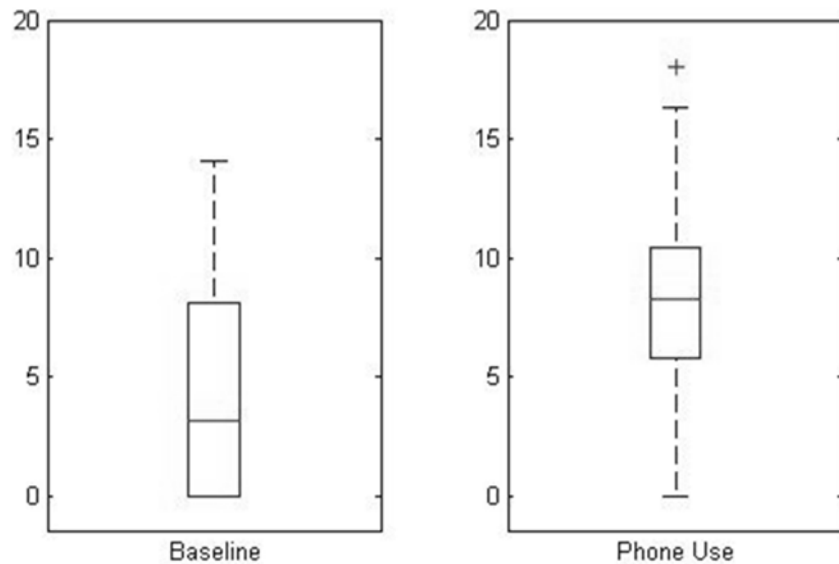


Figure 15: Peak brake pressure

Table 11: Peak brake pressure: Phone Use

SD Peak Brake Pressure	Mean of Means	SD
Baseline Segments	4.6	5.6
Secondary Task	8	5.2

3.2.4. Mean absolute relative velocity

Mean absolute relative velocity has been shown to significantly affect the logistic analysis (see Sections 2.9& 4.1.1). The standard deviation of the mean values from baseline segments was shown to be less than the standard deviation of secondary task segments. Secondary task segments also exhibited a higher mean value of 1.7 seconds against 1.4 seconds for baseline segments the difference in values being .3 seconds (see Table 11).

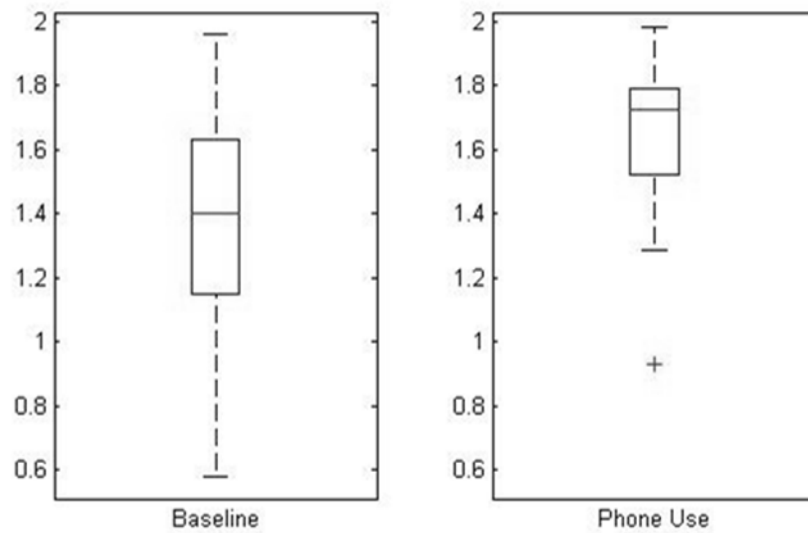


Figure 16: Mean absolute relative velocity

Table 12: Mean Relative Velocity: Phone Use

Mean Absolute Relative Velocity(km/h)	Mean of Means	SD of Means
Baseline Segments	1.3	0.33
Secondary Task	1.7	0.25

Figure 17 plots the mean of means of baseline trip segments against the mean of means of trip segments with phone use for the following measures:

- Peak steering angle acceleration
- SD steering angle acceleration
- Peak brake pressure
- SD longitudinal jerk
- SD longitudinal acceleration
- Mean absolute relative velocity

The mean values from baseline segments were observed to be lower than the mean values from secondary task segments for the variables presented in Figure 17.

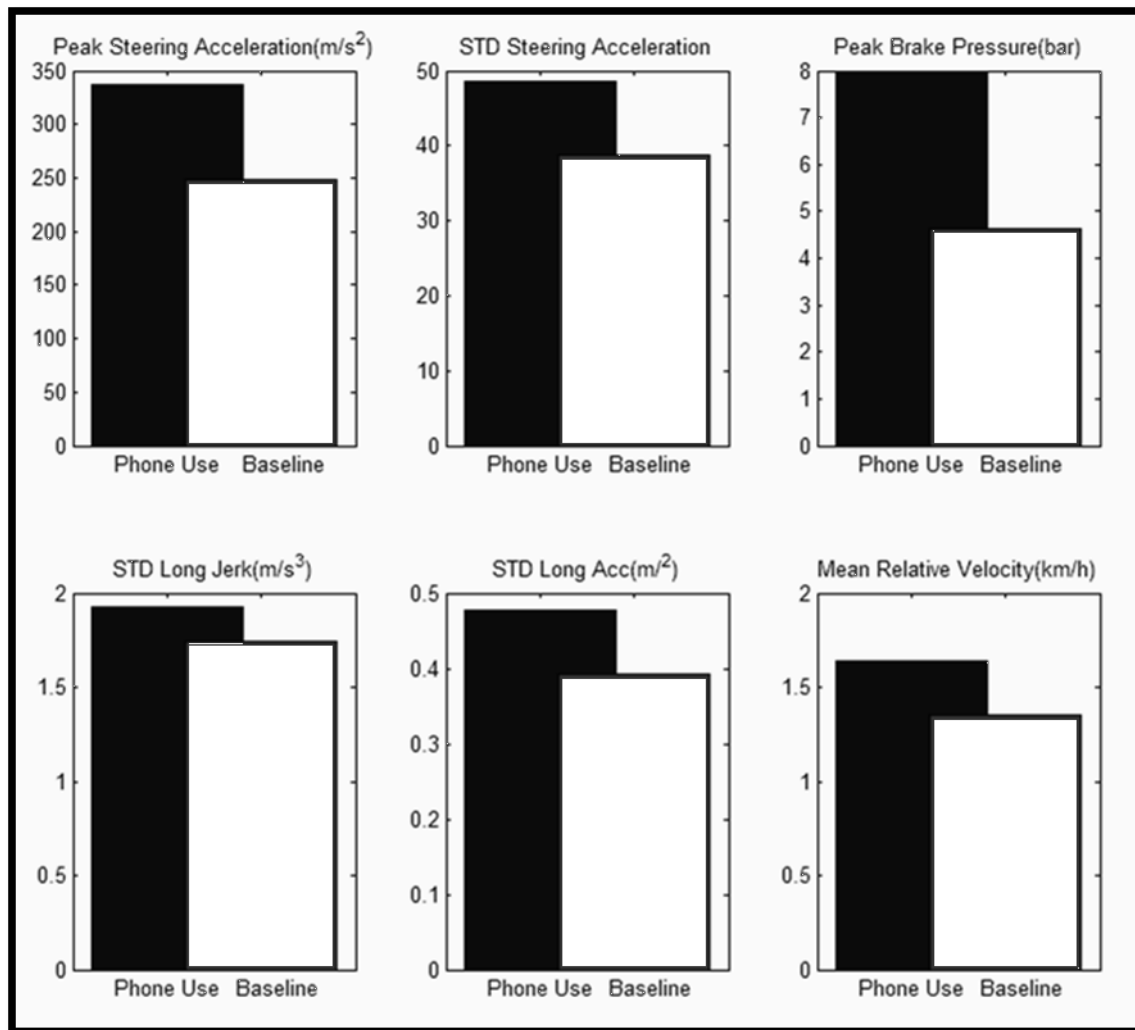


Figure 17: Mean of measures: Baseline segments vs. phone use

Standard deviation of the measures is shown in Figure 18. The trend here is not so clear with the standard deviation of peak brake pressure and mean absolute relative velocity of the baseline segments being higher than the segments with phone use. Other measures exhibit lower values of standard deviation than segments with phone usage.

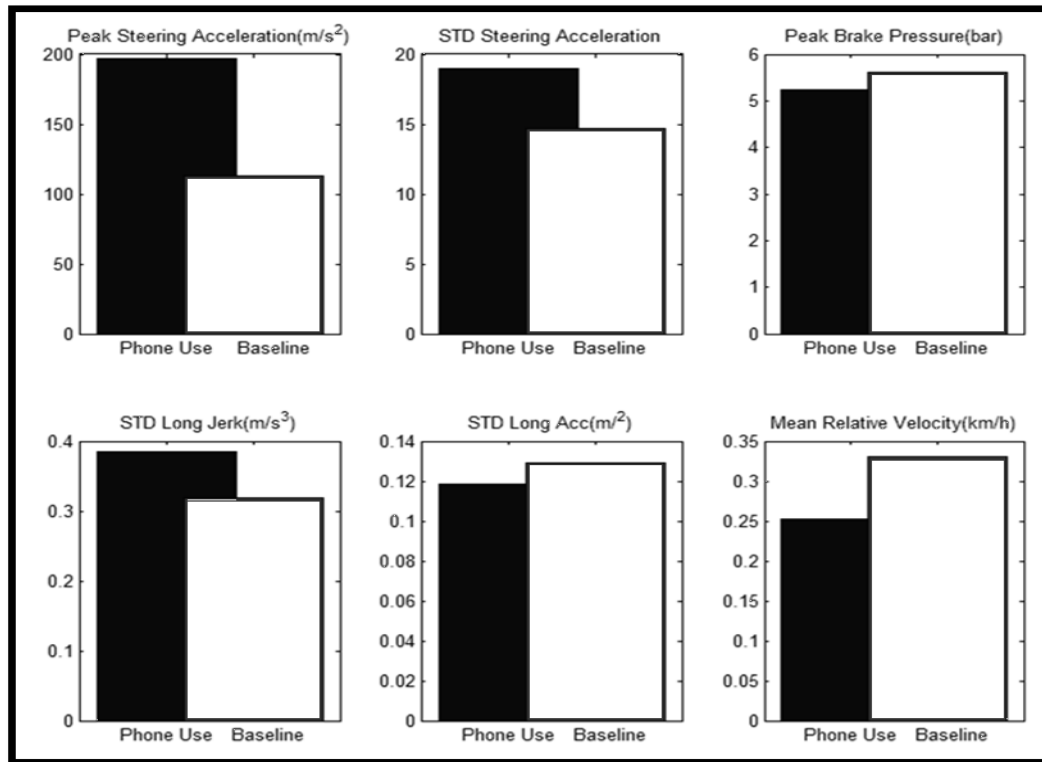


Figure 18: Standard deviation of measures: Baseline vs. Phone use

3.2.5. ADAS warnings

Warnings from the ADAS (FCW, BLIS, LDW, etc.) systems were not observed to affect driver headway selection or secondary task performance. A small difference of .16 seconds was noted between the mean headways of segments with ADAS warnings and the mean headway of segments without ADAS warnings. A T-test was used to test the alternative hypothesis that mean headway times of baseline and segments with ADAS warnings are significantly different. The null hypothesis in this case could not be rejected ($p > 0.05$).

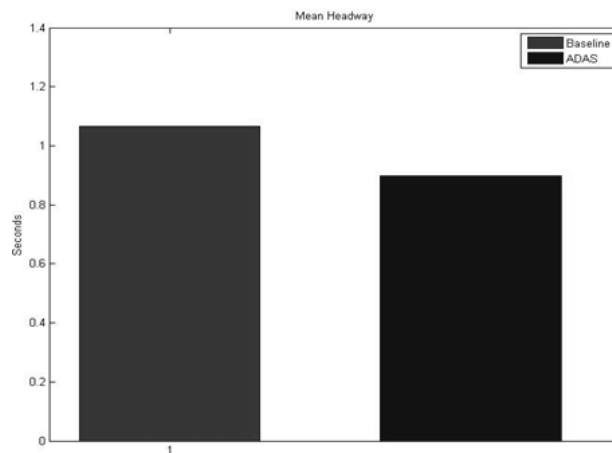


Figure 19: Mean headway: Baseline vs. ADAS segments

4. Discussion

4.1. Logistic regression analysis

Results of the logistic analysis seem to support previous findings (Horrey, 2004) which indicate secondary task performance during steady state car following affects the drivers response to critical (or potentially critical events) events such as sudden lead vehicle deceleration, more than continuous performance indicators.

4.1.1. Univariate logistic analysis

The univariate logistic analysis found several statistically significant measures when predicting phone use. The larger number of significant measures identified in the filtered dataset (see Table 3, column 4) may be attributed to the headway and relative velocity thresholds which selects only data from fully constrained car following situations where the driver may have been more inclined to perform secondary tasks than partially constrained situations where the drivers cognitive resources may have been more in demand. It was known that drivers in fully constrained car following situations tend to maintain a relative velocity below 3 km/h (McDonald, 1997) and headway times (Dunn, et al., 1994) of less than 2.5 seconds (See Section 2.9).

The increase in significant factors noted between filtered and unfiltered datasets may indicate an increase in compensatory control in fully constrained car following during phone use i.e. the driver pays more attention to following the lead vehicle while performing a secondary task. Relative velocity and headway time are therefore important factors affecting secondary task performance in steady state car following situations.

Significant measures (peak brake pressure, peak steering wheel acceleration etc.) are hypothesized to be related to secondary tasks in the sense that these values tend to peak in segments where a driver during a secondary task, glances away from the road more frequently than during baseline driving. This could lead to the driver having to compensate more frequently for any real or perceived change in the relative position of the lead vehicle. As suggested in the previous paragraph an alternative explanation is to attribute these measures to heightened concentration during secondary task performance.

Standard deviation of longitudinal jerk, acceleration, relative velocity and steering angle acceleration were found to be significant from the univariate analysis. Secondary task segments had a larger standard deviation than baseline segments for steering angle acceleration and longitudinal jerk while the reverse was true for relative velocity and longitudinal acceleration (see Figure 18). The smaller value of standard deviation in relative velocity may indicate a higher level of concentration and compensatory control during phone use. This is supported by the larger standard deviation noted in signals related to control particularly steering angle acceleration.

4.1.2. Multivariate logistic analysis

Measures found significant in the univariate analysis were found to remain significant in the multivariate logistic analysis. Steering angle measures were found to remain significant in a model that used all seven identified measures¹⁵ as predictors. This may indicate that steering angle measures are more relevant as indicators of compensatory control. Interaction effects from all tests were statistically insignificant indicating that the driver compensated during a secondary task by either braking or steering thus rendering insignificant the instances where both lateral and longitudinal control inputs were required.

4.2. T-test

Baseline and secondary task populations of measures¹⁶ were shown to be significantly different which supports an assertion that phone use induced changes in the compensatory control behaviour shown by the driver. The driver in this case felt an increased need to make control inputs to cope with a real or perceived change in the steady state following (e.g. lead vehicle deceleration). The higher mean values of independent variable measures seen from Figure 17 seems to support this. A similar trend was noted in the SD of measures; however peak brake pressure and relative velocity showed a reverse trend with the SD of phone use segments being lower than baseline segments (see Figure 18). As stated in section 4.1.1 this may indicate compensatory control and a higher degree of driver concentration. The driver in these sections exercised more control over brake pressure and relative velocity thus leading to smaller standard deviations of these measures.

It was interesting to note that measures, such as lane offset which has traditionally been used to study driving behaviour, did not show significant difference between baseline and secondary task segments. ADAS warnings were also found to not have a significant effect on driver headway behaviour.

4.3. Study limitations

The euroFOT database at SAFER is in a state of expansion as more field data is being uploaded intermittently. Due to the transient state of the database, the volume of driving data available for analysis dictated the selection of drivers and geographical study areas. The amount of usable data was thus limited. Although data was available from a total of approximately 20,000 valid trips, few drivers had logged enough data on the arterial road segments under study. Of these 25 drivers a point of interest is that only 2 drivers regularly performed secondary tasks while driving. This was partly expected as secondary tasks make up for a small percentage of trip time for most drivers. Other factors such as age and occupation may also have an effect on the chances that a driver would perform a secondary task while driving. An alternative explanation might be that the study drivers did not perform secondary tasks while in car following situation but during free driving situations.

¹⁵ From the logistic analysis

¹⁶ Significant measures identified from the logistic analysis

A considerable amount of data¹⁷ was excluded from the analysis due to the data being incomplete. Missing video data was the leading reason for data being excluded although a small percentage of trips were excluded due to missing variables. A small amount of data segments were excluded as the driver in the segment was someone other than the study driver. This is not unexpected as NDS's aim for as near real driving conditions as possible and this means imposing very few restrictions on the test subjects.

The test dataset was used to perform a number of statistical tests for a variety of variables. No correction was made for the number of tests performed.

Certain situations that might constitute secondary task performance were not considered to be such. These include instances of the driver concentrating on other objects in his forward view field such as signboards and other distractions and instances where the driver seems to have the leading vehicle in clear view but in fact has temporarily lost track of the leading vehicle as his cognitive resources are focussed elsewhere (an upcoming meeting etc.) – the 'Looking but not seeing' situation. While instances similar to the two described can be identified and studied from established patterns in driving data and with the use of eyetracker data this involves significantly more work and placed this type of analysis outside the bounds of this study.

4.4. Conclusion

The main findings of this study are listed below

- No measures reached significance when using the unfiltered dataset in both the logistic regression analysis and T-test analysis. When relative velocity and headway time filters were applied (See section 2.9) this resulted in several measures reaching significance. This may indicate increased compensatory control or the driver being more inclined to perform secondary tasks during fully constrained car following (See section 4.1.1).
- Univariate logistic regression analysis found seven measures to be significant. These measures were peak & SD steering angle acceleration, peak brake pressure, SD longitudinal jerk & acceleration, mean & SD relative velocity. These measures may all be interpreted as measures of compensatory control.
- Multivariate logistic regression analysis showed steering angle measures remained significant in a combined model of phone use using all available measures as predictors. Subsequent models using fewer predictors showed other significant measures¹⁸ also remained significant when not paired with more than one steering angle measure.
- The T-test analysis found baseline and phone use segments in all seven measures identified from the logistic analysis to be significantly different.

¹⁷ Approximately 20%

¹⁸ Measures found significant in the univariate logistic analysis.

In conclusion this study supports previous findings which suggest secondary tasks may have a greater effect on driver reaction time to critical events than normal driving. Identified measures which were shown to be statistically significant indicators of phone use are hypothesised to be related with reaction time to critical events.

4.5. Future work

The availability of a larger set of data than the one available for this thesis would greatly increase the statistical reliability of this study. Data from varied drivers and road segments would allow a cross comparison of results and greatly add to the utility of this study. More data would also allow an in depth analysis of the difference (if any) in effects of phone conversations and phone visual tasks in car following situations.

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Appendix A: (Independent Variables)

Steering wheel jerk rate

Steering wheel information is an important indicator of latitudinal control. Although its effect on headway is limited it might be interesting to note the variation of steering wheel angle in an attempt to quantify driver inattention levels. The variation in steering angle versus headway and distributions of steering angle between secondary task and non-secondary task segments are thus noted.

Yaw rate

The rate at which the vehicle is rotating about the vertical axis. Expressed in units of radians per second.

Lane offset

Distance from vehicle centre to the left or right marking. Measured as the distance from the forward facing camera.

Lateral acceleration and jerk

1st and 2nd derivatives of lateral velocity of subject vehicle. Obtained from the vehicles CAN bus.

Longitudinal acceleration and jerk

1st and 2nd derivatives of longitudinal velocity of subject vehicle. Obtained from the vehicles CAN bus.

Lead vehicle Velocity

Velocity of the lead vehicle in a steady state car following situation. Calculated from the radar information and the subject vehicle speed.

Subject vehicle velocity

Longitudinal velocity of the subject vehicle obtained from the CAN bus.

Relative velocity

Velocity relative to the lead vehicle.

Range

Distance from the vehicle radar to the lead vehicle calculated from the CAN bus radar information. This information was available from the database. Radar range was accurate up to a range of 150 metres. Range is a significant indicator of secondary effects on car following. A driver typically tries to maintain a fixed range. When the car in front brakes unexpectedly the range will decrease much more than usual. Therefore mean range is compared between secondary task and non secondary task segments. This correlates to reaction time to potentially critical events. It has been

found that secondary tasks normally lead to decreased reaction time to events. A measure of this may be the range keeping behaviour.

Brake pressure

Brake pressure is defined as the amount of pressure in the brake circuit and thus proportional to the amount of braking desired by the driver. Brakes are used only when necessary with the pressure being applied gradually in order to effect a reduction in the velocity while keeping the peak deceleration as low as possible. It was hypothesized that high peak values of brake pressure indicate situations where the driver was distracted by a secondary task.

Categorical performance indicators

Passenger indicators

The presence of passengers inferred from seat belt usage. Indicators of the four passenger seatbelts are fused to create one passenger flag.

FCW

The FCW system alerts the driver to an impending collision. Warnings however are rare despite a high level of usage in the test vehicles. Alerts from this system are relatively rare.

LDW and BLIS

The LDW system alerts the driver to an impending unexpected lane departure while the BLIS system alerts the driver to objects in the vehicles blind spots. Warnings from these systems could have an effect on headway time and are factors in this study.

Appendix B: (Matlab code)

1. Processing

```
Clear all
Close all
Clc
%
Cd('P:\Matlab\closedmat\Data\Driver_xx\Segment A\Range less than 100\')
Addpath('P:\Matlab\closedmat\Data\Driver_xx\Segment A\')
Addpath('P:\Matlab\closedmat\Data\Scripts')

Load Segmented
Counter = 0;

Files = fieldnames(Segmented.Driver_id_xx);
Driver = 'Driver_id_xx';

% LOADS TRIP FILE
For i = 1:length(files) % LOOPS THROUGH TRIPS
    Lanenames = fieldnames(Segmented.(Driver).(files{i}).Lane);
    For j = 1:length(lanenames) % LOOPS THROUGH LANES
        Vomeasuredatanames =
fieldnames(Segmented.(Driver).(files{i}).Lane.(lanenames{j}).vomeasuredata);
        Onoffnames = fieldnames(Segmented.(Driver).(files{i}).Lane.(lanenames{j}).onoff);
        Range = Segmented.(Driver).(files{i}).Lane.(lanenames{j}).vomeasuredata.mdistmainvhlahead;
        Vehspd = Segmented.(Driver).(files{i}).Lane.(lanenames{j}).vomeasuredata.mvehiclespeed;
        Distrav = Segmented.(Driver).(files{i}).Lane.(lanenames{j}).vomeasuredata.mdistancetraveled;
        Acc = Segmented.(Driver).(files{i}).Lane.(lanenames{j}).onoff.maccstate;
        Logic = logical(range <= 100 & vehspd >= 20 & (acc <= 1)); % LOGIC VECTOR

        If numel(logic)>1 %
(isempty(Segmented.(Driver).(files{i}).Lane.(lanenames{j}).vomeasuredata.mlatitude_GPS) ~= 1) &&
(Segmented.(Driver).(files{i}).Lane.(lanenames{j}).vomeasuredata.mdistancetraveled(end) -
Segmented.(Driver).(files{i}).Lane.(lanenames{j}).vomeasuredata.mdistancetraveled(1) > 10);%
distrav > 10 metres

% BUILDS AN INDEX VECTOR
        For k = 1:length(logic) % LOOPS THROUGH ALL DATA POINTS EACH TRIP
            If logic(k) == 0 % IF VALUE IS NAN OR DOES NOT FIT RANGE CRITERIA
                Index.(files{i}).(lanenames{j}).Ind(k) = nan; % CREATES NAN IN INDEX VECTOR
            Elseif logic(k) == 1 % IF VALUE IS NOT LESS THAN RANGE CRITERIA
                Index.(files{i}).(lanenames{j}).Ind(k) = k; % ENTERS THE CURRENT ITERATION
            INTO THE INDEX VECTOR. THE POSITIONS OF FIRST AND LAST VALUES ARE FOUND
            End
        End
        Index_values_to_save = findfirstandlast(Index.(files{i}).(lanenames{j}).Ind);
        If ~isempty(index_values_to_save) % IF DISTANCE VECTOR IS NOT EMPTY
            Lengthofindex = length(index_values_to_save);
            N = lengthofindex; % NUMBER OF TIMES FOR LOOP TO EXECUTE CALCULATED
            FROM THE INDEXLIST(CORRESPONDS TO NUMBER OF SEGMENTS)

            For k = 1:2:n % LOOPS THROUGH NUMBER OF SEGMENTS
                Firstvalue = index_values_to_save(k);
                Secondvalue = index_values_to_save(k+1);
                Minimumdistance = distrav(secondvalue)- distrav(firstvalue);
                If (minimumdistance > 50) %<-- TEST FOR MINIMUM DISTANCE OF SEGMENT
```

```

        Lanesegmentname = [lanenames{j} '_Segment' num2str(k) ];
        Counter = counter +1;

        For l = 1:length(vomeasuredatanames)
            Var1 =
Segmented.(Driver).(files{i}).Lane.(lanenames{j}).vomeasuredata.(vomeasuredatanames{l})(firstvalue
:secondvalue); % SAVES ALL FILES IN THE VOMEASUREDATA SUBSTRUCT

Saved.(Driver).(files{i}).Lane.(laneselementname).vomeasuredata.(vomeasuredatanames{l}) = var1;
        End

        For l = 1:length(onoffnames)
            Var2 =
Segmented.(Driver).(files{i}).Lane.(lanenames{j}).onoff.(onoffnames{l})(firstvalue:secondvalue); %
SAVES ALL FILES IN THE SEGMENT SUBSTRUCT
            Saved.(Driver).(files{i}).Lane.(laneselementname).onoff.(onoffnames{l}) = var2;
        End

        Plotname = [(files{i}) ' ' (laneselementname)];

        Figure(2)

        Plot(Saved.(Driver).(files{i}).Lane.(laneselementname).vomeasuredata.mlongitude_GPS,Saved.(Driver
).(files{i}).Lane.(laneselementname).vomeasuredata.mlatitude_GPS,'disp',(plotname))
        Hold on

        Saved.Driver_id_xx.(files{i}).osegmentinfo =
Segmented.(Driver).(files{i}).osegmentinfo;
        End
        End
        End
        End
    End
End

Save Stage2 Saved

```

2 . Extract Videos

```

clear all
close all
clc
cd('D:\Videos') % segment A
addpath('P:\Matlab\ClosedMat\Data\Driver_xx\Segment A\Range less than 100\')
addpath('P:\FOTware\v.3.7\VideoIO')

load Stage2
files = fieldnames(Saved.Driver_id_xx);

for i = 1:length(files); % plotting commands
    segmentnames = fieldnames(Saved.Driver_id_xx.(files{i}).Lane);

    for j = 1:length(segmentnames)
        %
        filepath = ['K:' Saved.Driver_id_xx.(files{i}).oSegmentInfo.voVideoSources(1,2).sRelativePath
];% (1,1) road cam (1,2) driver cam <-----CHOOSE CAMERA
        %
        videopath = (filepath);
    end
end

```

```

%
if exist(videopath,'file')
%     segmentnames = fieldnames(Saved.Driver_id_xx.(files{i}).Segment);
a =
isfinite(Saved.Driver_id_xx.(files{i}).Lane.(segmentnames{j}).voMeasureData.mVideo1Indices);
vector =
Saved.Driver_id_xx.(files{i}).Lane.(segmentnames{j}).voMeasureData.mVideo1Indices; % 1
DRIVER CAM, 0 ROAD CAM <-----CHOOSE INDEX VECTOR
Video.(files{i}).(segmentnames{j}).mov = videoread((filepath),vector);
VideoName = ['Driver cam' files{i} segmentnames{j}];
movie2avi(Video.(files{i}).(segmentnames{j}).mov, (VideoName))
clear Video
%     figure(1)
plot(Saved.Driver_id_xx.(files{i}).Lane.(segmentnames{j}).voMeasureData.mSteeringAngleJerkRate,'
disp',files{i})
%     hold on
end
end
end
end

```

3 . Creates dataset with selected measures and calculates statistics

```

close all
clear
clc
cd('P:\Matlab\ClosedMat\Data\Driver_xx\Segment A\Range less than 100')
load Stage2 % LOADS DATA FILE
files = fieldnames(Saved.Driver_id_xx);
data = dataset; % CREATES DATASET
counter = 0;

for i = 1:length(files) % LOOPS THROUGH FILES
    segmentnames = fieldnames(Saved.Driver_id_xx.(files{i}).Lane); % CREATES CELL WITH
    SEGMENTNAMES
    counter = counter + 1;
    for j = 1:length(segmentnames) % LOOPS THROUGH SEGMENTS
        Trip = files{i};
        segment = segmentnames{j};

        % MEANS
        mYawRate =
        nanmean(abs(Saved.Driver_id_xx.(Trip).Lane.(segment).voMeasureData.mYawRate));
        mSteeringAngleJerk =
        nanmean(abs(Saved.Driver_id_xx.(Trip).Lane.(segment).voMeasureData.mSteeringAngleJerk));
        mSteeringAngleJerkRate =
        max(abs(Saved.Driver_id_xx.(Trip).Lane.(segment).voMeasureData.mSteeringAngleJerkRate));
        PeakLatAcc =
        max(abs(Saved.Driver_id_xx.(Trip).Lane.(segment).voMeasureData.mLateralAcc));
        mLateralJerk
        =max(abs(Saved.Driver_id_xx.(Trip).Lane.(segment).voMeasureData.mLateralJerk));
        PeakLongAcc =
        max(abs(Saved.Driver_id_xx.(Trip).Lane.(segment).voMeasureData.mLongAcc));
        mLongJerk = max(abs(Saved.Driver_id_xx.(Trip).Lane.(segment).voMeasureData.mLongJerk));
        mLeftLaneOffset =
        nanmean(abs(Saved.Driver_id_xx.(Trip).Lane.(segment).voMeasureData.mLeftLaneOffset));
        mRightLaneOffset =
        nanmean(Saved.Driver_id_xx.(Trip).Lane.(segment).voMeasureData.mRightLaneOffset);
    end
end

```



```

MeanVehSpd =
nanmean(Saved.Driver_id_xx.(Trip).Lane.(segment).voMeasureData.mVehicleSpeed);
MeanRange =
nanmean(Saved.Driver_id_xx.(Trip).Lane.(segment).voMeasureData.mDistMainVhlAhead);
MeanHeadway = nanmean(Saved.Driver_id_xx.(Trip).Lane.(segment).voMeasureData.mTHW);
MeanVelVehAhead =
nanmean(Saved.Driver_id_xx.(Trip).Lane.(segment).voMeasureData.mVelMainVhlAhead);
RelVelMainVhlAhead =
nanmean(abs(Saved.Driver_id_xx.(Trip).Lane.(segment).voMeasureData.mRelVelMainVhlAhead));%
negative values
AccelPedalPos =
nanmean(Saved.Driver_id_xx.(Trip).Lane.(segment).voMeasureData.mAccelPedalPos);
BrakePressure =
max(Saved.Driver_id_xx.(Trip).Lane.(segment).voMeasureData.mBrakePressure);

mSteeringAngle =
nanmean(abs(Saved.Driver_id_xx.(Trip).Lane.(segment).voMeasureData.mSteeringAngle));

% MEANS OF PASSENGER INDICATORS
% Passenger = nanmean(Saved.Driver_id_xx.(Trip).Lane.(segment).OnOff.mPassengerBuckled);
% RearBuckLeft =
nanmean(Saved.Driver_id_xx.(Trip).Lane.(segment).OnOff.mRearBuckleLeft);
% RearBuckMid =
nanmean(Saved.Driver_id_xx.(Trip).Lane.(segment).OnOff.mRearBuckleMid);
% RearBuckRight =
nanmean(Saved.Driver_id_xx.(Trip).Lane.(segment).OnOff.mRearBuckleRight);

Passenger =
max((Saved.Driver_id_xx.(Trip).Lane.(segment).OnOff.mPassengerBuckled)+(Saved.Driver_id_xx.(T
rip).Lane.(segment).OnOff.mRearBuckleLeft)+(Saved.Driver_id_xx.(Trip).Lane.(segment).OnOff.mR
earBuckleMid)...
+(Saved.Driver_id_xx.(Trip).Lane.(segment).OnOff.mRearBuckleRight));

% PEAK VALUES
% DisTrav =
max(Saved.Driver_id_xx.(Trip).Segment.(segment).voMeasureData.mDistanceTraveled)/1000; %
DISTANCE TRAVELLED IN KILOMETRES
% laneposition =
std(abs(Saved.Driver_id_xx.(Trip).Lane.(segment).voMeasureData.mLeftLaneOffset));

% SYSTEMS
mADASWarning =
max((Saved.Driver_id_xx.(Trip).Lane.(segment).OnOff.mBLISLeftWarning)+(Saved.Driver_id_xx.(T
rip).Lane.(segment).OnOff.mBLISRightWarning)+(Saved.Driver_id_xx.(Trip).Lane.(segment).OnOff.
mLDWWarning)...
+(Saved.Driver_id_xx.(Trip).Lane.(segment).OnOff.mFCWWarning));
%
% mLDWWarning = max(Saved.Driver_id_xx.(Trip).Lane.(segment).OnOff.mLDWWarning);
% mBLISLeftWarning =
max(Saved.Driver_id_xx.(Trip).Lane.(segment).OnOff.mBLISLeftWarning);
% mBLISRightWarning =
max(Saved.Driver_id_xx.(Trip).Lane.(segment).OnOff.mBLISRightWarning);
% mFCWWarning = max(Saved.Driver_id_xx.(Trip).Lane.(segment).OnOff.mFCWWarning);
Trip_id = Trip;
segmentid = segment;

plotname = [(Trip_id) (segmentid)];

```

```

data = [data;
dataset(MeanVehSpd,MeanRange,MeanHeadway,MeanVelVehAhead,RelVelMainVhlAhead,
AccelPedalPos,BrakePressure,mYawRate,Daylight,...

mSteeringAngle,mSteeringAngleJerk,mSteeringAngleJerkRate,Passenger,PeakLatAcc,mLateralJerk,...
    PeakLongAcc,mLongJerk,mLeftLaneOffset,mRightLaneOffset,mADASWarning... %
mAmbientLightCond,mACCState,{nominal(Trip_id),'Trip'},{nominal(segmentid),'Segment'}}]; %
DISTANCE IN METRES,SPEED IN KMPH
    end
end

% export(data,'XLSfile','data')

```

4 . Logistic regression example (standard deviations - with filtered data - headway < 2.5 seconds)

```

close all
clear
clc

cd 'G:\Thesis\FromFOTNet'

data = dataset('XLSFile','TEST_DATASET_1');

Secondary_tasks = data.Secondary_Tasks_Combined((data.MeanHeadway < 2.5));

Predictors(:,1) = data.STDYawRate((data.MeanHeadway < 2.5));
Predictors(:,2) = data.STDSteeringAngleAcceleration((data.MeanHeadway < 2.5));
Predictors(:,3) = data.STDSteeringAngleVelocity((data.MeanHeadway < 2.5));
Predictors(:,4) = data.STDLatAcc((data.MeanHeadway < 2.5));
Predictors(:,5) = data.STDLatJerk((data.MeanHeadway < 2.5));
Predictors(:,6) = data.STDLongAcc((data.MeanHeadway < 2.5));
Predictors(:,7) = data.STDLongJerk((data.MeanHeadway < 2.5));
Predictors(:,8) = data.STDLaneOffset((data.MeanHeadway < 2.5));
Predictors(:,9) = data.Passenger((data.MeanHeadway < 2.5));
Predictors(:,10) = data.ADASWarning((data.MeanHeadway < 2.5));
Predictors(:,11) = data.MeanHeadway((data.MeanHeadway < 2.5));
Predictors(:,12) = data.STDHeadway((data.MeanHeadway < 2.5));

Predictors(:,13) = data.PeakBrakePressure((data.MeanHeadway < 2.5));
Predictors(:,14) = data.STDBrakePressure((data.MeanHeadway < 2.5));
Predictors(:,15) = data.ButtonPressed((data.MeanHeadway < 2.5));
Predictors(:,16) = data.MeanRange((data.MeanHeadway < 2.5));
Predictors(:,17) = data.MeanEgoVel((data.MeanHeadway < 2.5));

[coefficient_estimates,deviance,stats] = glmfit(Predictors,Secondary_tasks,'binomial');

```

Appendix C :(Results)

Logistic Regression

Table 13: Univariate Logistic Analysis - Phone Usage

Measure	P values	
	Unfiltered dataset	Headway < 2.5, Relative velocity < 2
Peak Steering Angle Acceleration	0.2348	0.0197
SD Steering Angle Acceleration	0.1848	0.0251
SD Abs Steering Angle Acceleration	0.2166	0.0331
Mean Steering Angle Velocity	0.5561	0.0508
SD Steering Angle Velocity		0.1046
Mean Headway time	0.0314	0.1219
Peak Brake Pressure	0.0252	0.0311
SD Brake Pressure	0.0475	0.1022
SD Long Jerk	0.1448	0.0462
Max Abs Long Acc		0.1555
SD Long Acc	0.3694	0.0173
Mean Abs Rel Vel	0.9963	0.0020
SD Rel Vel	0.1155	0.0039

Table 14: Univariate Logistic Analysis - Any Secondary Task

Measure	P values
Peak Steering Angle Acceleration	0.0469
SD Steering Angle Acceleration	0.0283
SD Abs Steering Angle Acceleration	0.0483
Mean Steering Angle Velocity	0.0629
SD Steering Angle Velocity	0.1561
Mean Lane Offset	0.1303
Mean Abs Rel Vel	0.0198
SD Rel Vel	0.0341
SD Longitudinal Acceleration	0.0851
SD Long Jerk	0.1368

ROC curves – Significant Factors

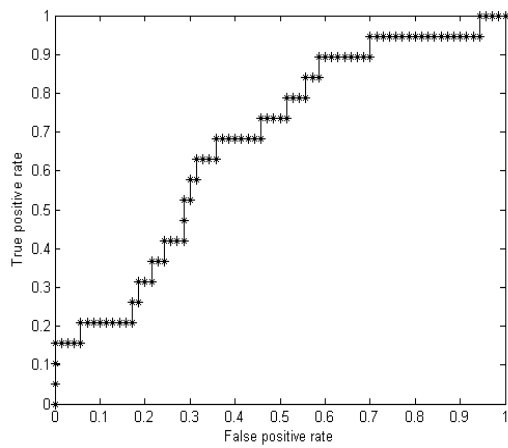


Figure 22: ROC: SD Steering angle acceleration

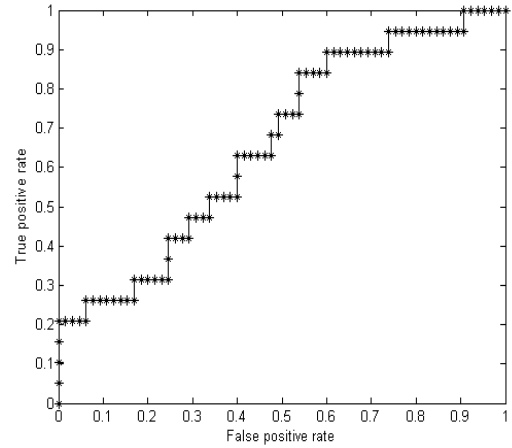


Figure 23: ROC: SD Steering Angle Velocity

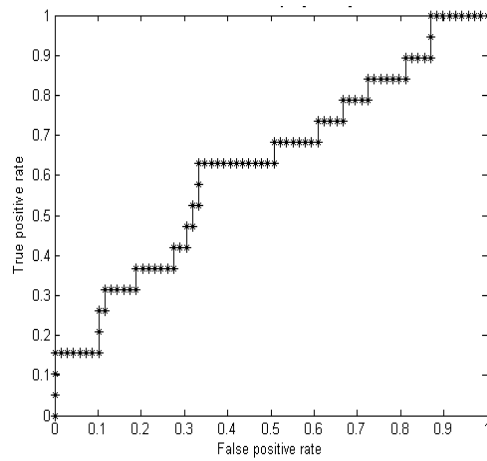


Figure 22: ROC: Mean Headway

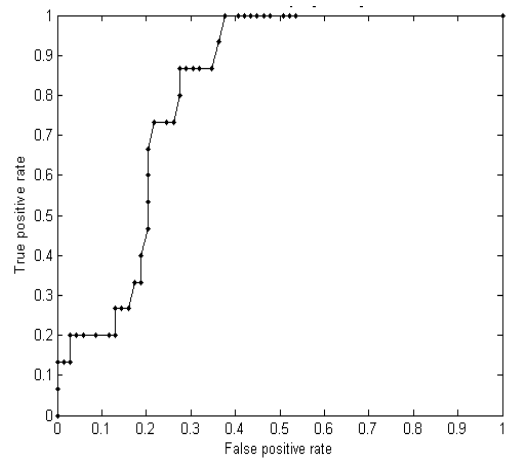


Figure 22: ROC: Peak brake pressure

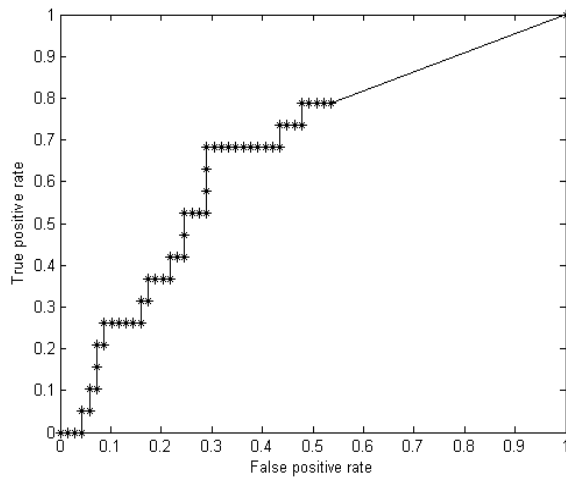


Figure 27: ROC: SD brake pressure

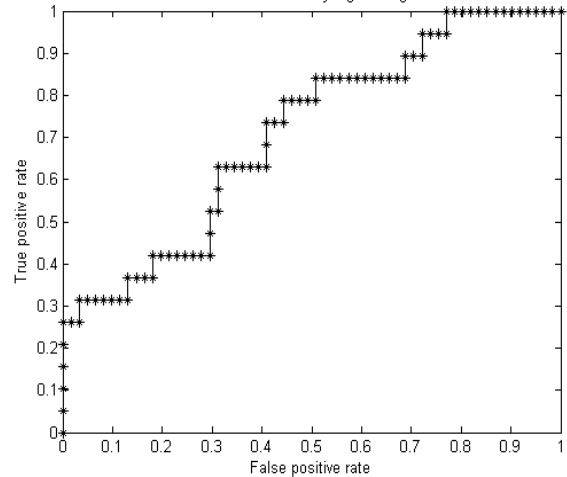


Figure 27: ROC: Peak steering angle acceleration

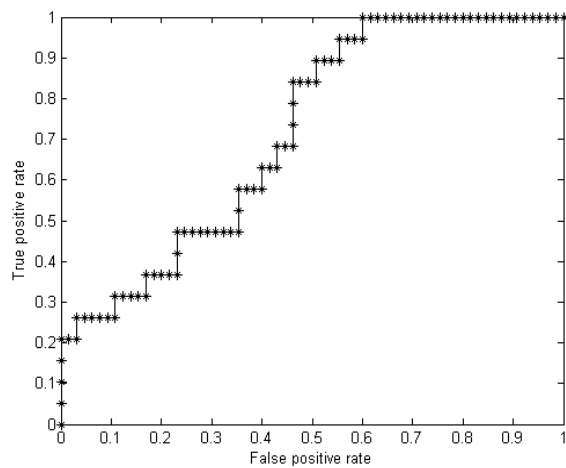


Figure 27: ROC: SD longitudinal jerk

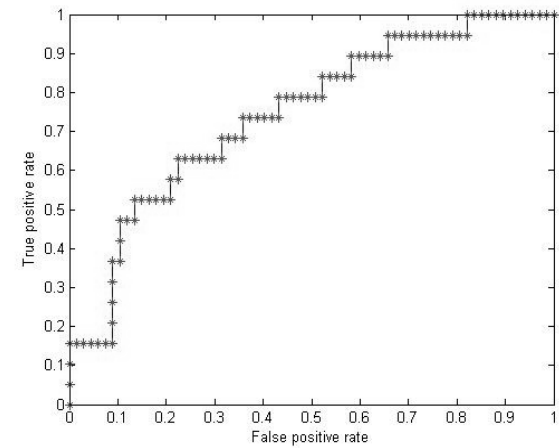


Figure 27: ROC: SD longitudinal acceleration

Table 15: AUC (Significant factors and factors close to significance)

Measure	AUC
Peak steering angle acceleration	0.71
SD steering angle acceleration	0.67
Mean steering angle velocity	0.72
SD steering angle velocity	0.66
Mean Headway time	0.62
Peak brake pressure	0.81
SD brake pressure	0.67
SD longitudinal jerk	0.71

Max longitudinal acceleration	0.65
SD longitudinal acceleration	0.74
Mean relative velocity	0.89
SD relative velocity	0.72

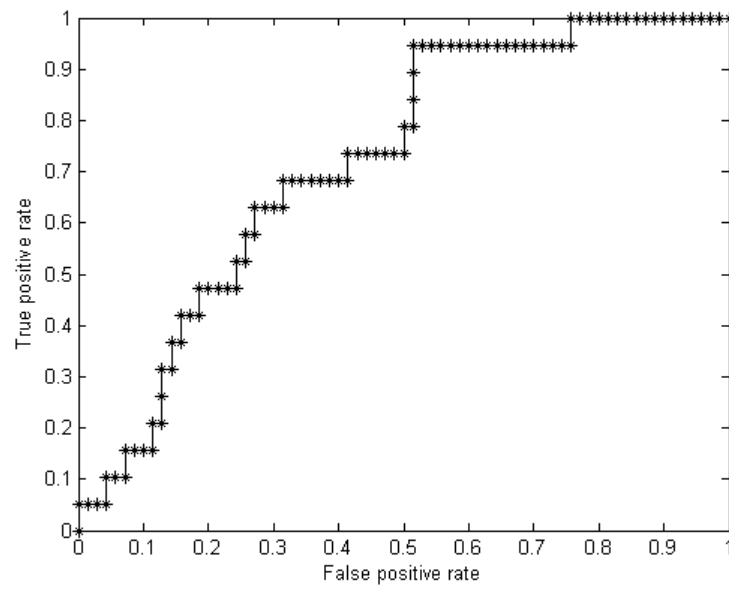


Figure 28: ROC curve: SD relative velocity

ROC curves – Non-Significant Factors

Table 16: AUC (Non-Significant Factors)

Measure	AUC
MeanAbsYawRate	0.50
MaxAbsYawRate	0.51
SD Yaw Rate	0.49
MaxAbsLatAcc	0.51
STDLatAcc	0.53
MaxAbsLatJerk	0.49
STDLatJerk_1	0.48
STDLaneOffset	0.51
MaxAbsLongJerk	0.53
STDHeadway	0.50
MeanEgoVel	0.49
MeanLeadVel	0.53

SD Longitudinal Jerk

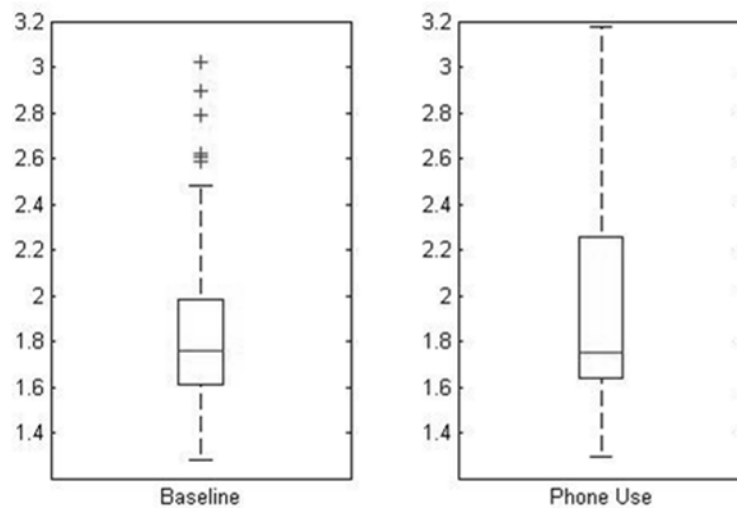


Figure 29: SD Longitudinal jerk

Table 17: AUC (Non-Significant Factors)

SD Longitudinal Acceleration	Mean of Means	SD
Baseline Segments	1.74	0.32
Secondary Task	1.92	0.38

SD Longitudinal Acceleration

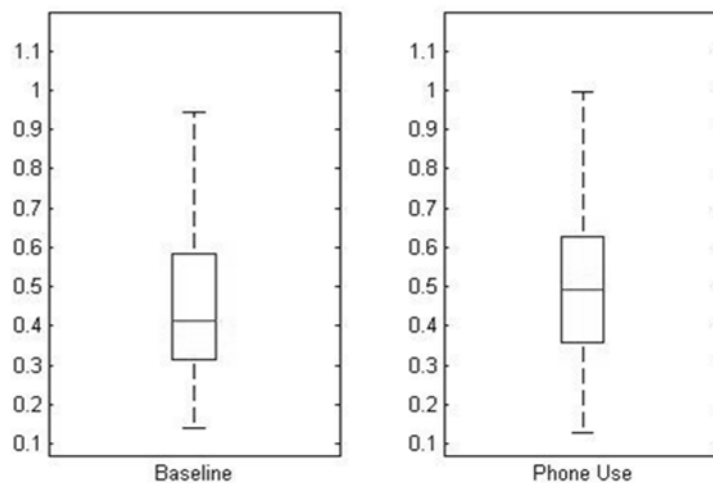


Figure 30: SD Longitudinal acceleration

Table 18: AUC (Non-Significant Factors)

SD Longitudinal Acceleration	Mean of Means	SD
Baseline Segments	0.41	0.2
Secondary Task	0.49	0.25