KNOWLEDGE IN ACTION

School of Transportation Sciences

Master of Transportation Sciences

Master's thesis

How to identify dangerous overtaking manoeuvres based on real-time sensor data?

Trang Thanh Kieu Nguyen

Thesis presented in fulfillment of the requirements for the degree of Master of Transportation Sciences, specialization Traffic Safety

SUPERVISOR :
Prof. dr. Tom BRIJS

CO-SUPERVISOR :
dr. Muhammad ADNAN

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KNOWLEDGE IN ACTION

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Disclaimer

This master thesis was written during the COVID-19 pandemic in 2020-2021 that might have had an impact on the writing process, the research activities and the research results.

Preface

Overtaking manoeuvre which involves both lateral and longitudinal control is considered as one of the most dangerous and complex manoeuvres that a driver can perform. The reason is that most of traffic accidents are caused by human misbehaviours such as driver cognitive overload, judgement mistake and operation errors. In all types of road accidents related to overtaking manoeuvres, there is a risk of rear-end accidents that the overtaking vehicle no longer maintains the safe distance from the car ahead in preparation for overtaking. The research is an effort to contribute to the development of an Advanced Driver Assistance System which helps predict dangerous overtaking manoeuvres with respect to rear-end accidents before the headway between the driven and preceding vehicles reaches its critical threshold and alert the driver about these possible dangers, giving him enough time to react. A sensory-fusion deep learning architecture based on Recurrent Neural Networks (RNNs) with Long Short-Term Memory (LSTM) units is proposed to monitor vehicle dynamics and driving context and signal predictions. The prediction performance of regular LSTM-RNN and bidirectional LSTM-RNN are also compared with other models based on Feedforward neural network (FFNN). In term of experiment settings, the model is trained in simulation with driving scenarios on two-lane rural roads but is tested in natural freeway and city driving. The study also indicates implications and relevance of the constructed model in real-world application as well as current limitations and directions for future research.

The thesis with the topic “How to identify dangerous overtaking manoeuvres based on real-time sensor data?” marks a culmination of my study in the program of Master of Transportation – Traffic Safety Specialization at Hasselt University in the academic year 2020-2021. First and foremost, I would like to express my gratitude to the Creator of life for giving me the strength and courage to successfully complete the program, along with all the blessings and lessons learned in the last two years. Secondly, I gratefully acknowledge the funding opportunity received from VLIR-UOS in the pursuit of this master’s degree. Thirdly, I wish to express my sincere thanks to my supervisor, Prof. Dr. Tom Brijs who introduced me into this interesting research topic and has guided me in the right direction. Besides, I would like to express my great appreciation to my co-supervisor, Dr. Muhammad Adnan who has provided me with profound advices and knowledge sources on the research problem. One more time, sincere thanks go to Dr. Muhammad Adnan and his colleague, Bart De Vos for helping me set up the simulation experiment and operate the naturalistic driving experiment, especially under the difficult circumstance of coronavirus pandemic. In addition, my special regard also goes to my friend, Nguyen Do who enthusiastically participated in my experiments. Without their support, this dissertation would not be completed. I also wish to thank all the professors in the Master of Transportation department of Hasselt University who gave me necessary knowledge to write this dissertation, as well as to send a thank you to Hasselt University in general for free access to MATLAB software and reading materials used in the study period. Last but not least, I wish to acknowledge the encouragement of my family and my friends who dedicated their time with me and kept me going on this work.

Abstract

Most of traffic accidents are caused by human misbehaviours such as driver cognitive overload, judgement mistake and operation errors (Yang and Wang, 2007; Bellis and Page, 2008; Martinez et al., 2017). Overtaking is therefore considered as one of the most dangerous and complex manoeuvres where the driver needs to be assisted the most with the help of Advanced Driver Assistance Systems. Our research scope is limited to developing a prediction model of dangerous overtaking with respect to rear-end accidents on two-lane roads.

Our study focuses on the preparation phase of overtaking before a significant lateral change to the left of the vehicle. The total of 40 and 28 legitimate overtaking manoeuvres were respectively recorded in simulation driving for model training, internal validation and testing purposes and in naturalistic driving in Hasselt city for further testing purposes. Four interested variables, including longitudinal speed, longitudinal acceleration, steering wheel/heading angular rate and headway between the driven vehicle and the preceding vehicle are extracted and interpolated. In this research, a sensory-fusion deep learning architecture based on Recurrent Neural Networks (RNNs) with Long Short-Term Memory (LSTM) units is proposed to monitor vehicle dynamics and driving context and predict dangerous overtaking manoeuvres with respect to rear-end collisions at 1-2s before the headway reaches its threshold of 1.2s with the performance accuracy of about 80%. This LSTM-RNN based system fuses multiple sensory streams from driving context and vehicle dynamics, models long temporal dependencies in a sequence-to-sequence prediction manner, learns to anticipate using only a partial temporal context and predict the dangerous overtaking before it is performed. The performance of three types of neural networks, including Feedforward shallow neural network (FFNN), regular LSTM-RNN and bidirectional LSTM-RNN are also compared and data pre-processing is required to build different input and output formats for training process in different neural network applications in MATLAB. Different from LSTM-RNN based methods which have a neural network layer for fusing the temporal streams of data coming from different sensors, the non-sequence-based method of FFNN uses a simple sensory approach of concatenation of feature vectors instead. The results are in line with previous works, showing that the Bi-LSTM-RNN based model outperforms in prediction performance because of its advantages in modelling temporal context and using all available input information in the past and future of a specific time framework for prediction. The study also found out that drivers are more likely to violate the safe headway rule in urban areas rather than in rural roads; changing the overtaking strategies does not help to increase the chance of avoiding rear-end collisions; speed is an important feature contributing to the early and accurate prediction while the steering wheel/heading feature only helps increase the prediction performance after their turning-points which can be used in manoeuvre recognition rather than prediction models. In general, the study shows that although the model is trained in simulation with driving scenarios on two-lane rural roads, the model testing in natural freeway and city driving with the relatively high prediction accuracy regardless of overtaking strategies indicates a high possibility for model standardization.

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List of abbreviations

ACC	Adaptive Cruise Control
ADAS	Advanced Driver Assistance System
ANN	Artificial Neural Network
(Bi)LSTM-RNN	(Bidirectional) Long Short-term Memory – Recurrent Neural Network
DII	Driver Intention Inference
FCW	Forward Collision Warning
FFNN	Feedforward Neural Network
HMM	Hidden Markov Model
LDW	Lane Departure Warning
OAS	Overtaking Assistance System
SVM	Support Vector Machine

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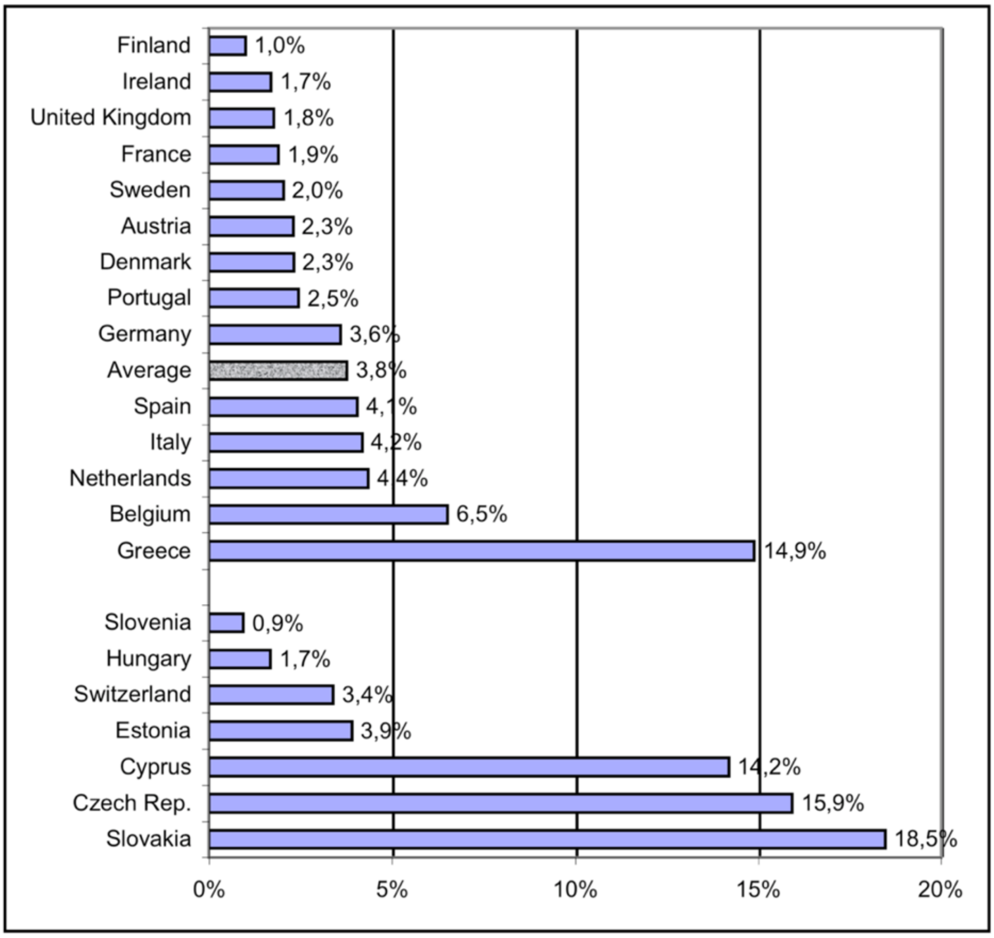
Chapter 1: Introduction

1.1 Statement of problem

Overtaking safety problems

As driver's error, among other factors, shares the highest proportion (75%) in contributing to crash occurrence (Vogel and Bester, 2005), overtaking involving both lateral and longitudinal control is considered as one of the most dangerous and complex manoeuvres that a driver can perform. Indeed, overtaking on roads with oncoming traffic is one of the most difficult driving tasks (McKnight and Adam, 1970). As shown in Figure 1.1, the study of self-reported driver behaviour in Europe indicated that risky overtaking is typical among samples in Slovakia, Czech Republic, Greece and Cyprus (SARTRE3, 2004). National policies on overtaking vary with general prohibitions of overtaking of different vehicle types, on different categorized roads, for certain times or distance. However, a Dutch study showed that 20% of overtaking manoeuvres were still observed on sections with an overtaking prohibition (Hegeman, 2004). Therefore, dangerous overtaking is among the most targeted traffic violation by police in Europe (Makinen et al., 2003).

Figure 1. 1. The frequency of self-reported overtaking when respondents think "just make it"



Source: SARTRE3 (2004)

In the seventies, 43% of all traffic accidents on two-lane highways involved overtaking or passing manoeuvres (Kemper et al., 1972), making overtaking as the fifth most common cause of road traffic accidents (IDBRA, 1973). Clarke et. al (1998) classified road accidents involving overtaking manoeuvres into ten types and discussed three in detail, including collision with a right-turning vehicle, head-on collision and the 'return-and-lose-control' accident. There is also a risk of rear-end accidents that the overtaking vehicle no longer maintains the safe distance from the car ahead in preparation for overtaking (Rajalin et al., 1997). Also, the percentage of passenger vehicles involved in lane change crashes was the highest among other vehicle types, ranging up to 89.7% (Wang and Knipling, 1994). Naranjo et al. (2008) believed overtaking accidents are mainly resulted from failing to leave enough distance, overtaking when there was poor visibility, or not giving way to an overtaking vehicle. Mota et al. (1998) indicated the driver's focus only on his way forwards without the attention to the rear-view mirror makes the overtaking manoeuvre risky. Moreover, Gordon and Mart (1968) claimed that it is unable for drivers to estimate the overtaking distances and safety margins correctly because the speed of the involved vehicles, especially the overtaken vehicle, are not constant. Mosedale and Purdy (2004) reported that erroneous speed choice is a contributory factor to 18% of UK rural road accidents involving risky overtaking manoeuvres. Clarke et. al (1998) also found that differences in overtaking manoeuvres are a function of driver age. Afshin et al. (2010) also agreed that younger drivers (18-28 years old) with less than 2-year driving experience are most likely to be at fault in overtaking crashes. In general, Farah et al. (2009) analysed drivers' passing decisions on 2-lane rural highways and found that the most important factor affecting the measurement of overtaking risk by drivers is traffic-related variables, followed by geometric design and driver characteristics.

Within Europe, 25% of fatal crashes in Organization for Economic Cooperation and Development (OECD) member countries are head-on collisions that overtaking may be the main cause (OECD, 1999). In the US, 20% of all fatal crashes on two-lane rural roads, making up about 4500 fatalities annually, were crashes with oncoming traffic (Persaud et al., 2004). Between 2004-2008, there were other 336,000 crashes involved in lateral control manoeuvres such as overtaking and lane changing as a result of drivers' distraction or inappropriate decision making, representing a significant proportion of the total accidents (Najm et al., 2013). In the Netherlands, 2.6% of the total number of traffic fatalities was caused by overtaking on two-land rural roads (SWOV, 2003). In the UK, 7.9% of the fatal traffic accidents are estimated to be caused by overtaking on two-lane roads (Clarke et al., 1998). In Saudi Aribia, illegal overtaking is the second most frequent cause of traffic accidents after speeding and accounted for 10% of total accidents in 2001 (Nedal, 2004). Another study of overtaking in Iran showed that 20% of crashes which takes place on non-separated two-way two-lane rural roads were due to improper overtaking but these crashes accounted for 50% of fatalities, implying the seriousness of these overtaking-related crashes (Afshin et al., 2010). Table 1.1 shows the overview of other country specific overtaking accident findings.

Table 1. 1. Overview of country specific overtaking accidents' findings

Country	Findings
Denmark (Larsen, 2004)	Between 1986 and 1995, an average of almost 130 fatalities have been recorded each year in connection with head-on collisions, accounting for more than 20% of all fatalities

Finland (Katila and Keskinen, 2000)	When traffic accidents are divided into the groups “same driving direction”, “intersection” and “opposing driving direction”, 72% of accidents can be grouped in the last category
The Netherlands (AVV Transport Research Centre, 2002)	One third of all accidents between trucks and cars on roads outside built-up areas with a speed limit of 50, 80 or 100 km/h are frontal, indicating that overtaking may be the cause
Nottinghamshire, UK (Clarke et al., 1997)	Of 970 analysed accidents, 8% were caused by overtaking, representing 20% of the total fatalities. One of five most frequent accident scenarios is overtaking on a hill where overtaking is prohibited
Nottinghamshire, UK (Clarke et al., 1999)	Misjudgement of speed and distance to oncoming vehicles accounts for on average 8% of overtaking accidents. Highest dangers for overtakers come from oncoming vehicles that are not seen and from unexpected actions of overtaken vehicles
United Kingdom (DETR, 2000)	The number of accidents caused by overtaking manoeuvres is only 3.5% but assumed to be overrepresented in fatality statistics because of the high speeds at which they occur.
South Africa (Vogel and Bester, 2005)	Overtaking was identified as the main factor behind human error that causes 75% of the analysed accidents

Source: Adopted from Hegeman (2005)

Overtaking assistance systems

Advanced Driver Assistance Systems (ADAS) is a series of fast-developing techniques designed for allowing driving tasks more safely, more comfortably and more efficiently (Masikos et al., 2013). Nowadays, several of these systems, such as advanced cruise control, lane keeping assistance and back spot monitoring are already standard in many production vehicles in alerting drivers whenever they commit a dangerous manoeuvre (Broek et al., 2011). The high percentage of traffic accidents and fatalities in overtaking and lane change manoeuvres has given the rise to the need for the development of overtaking assistance systems (OAS) (Hegeman, 2008). Indeed, drivers would like to have some assistance with overtaking (Houtenbos et al., 2005a). Hegeman (2005) identified opportunities for developing potential overtaking assistance by dividing the overtaking task into 5 phases with 20 subtasks, each requiring different according assistance.

Early developments towards an overtaking assistant began around 2003 that Mitsubishi Proudia in Japan developed a system intended as a lane change assistance system for use in motorway driving (STARDUST, 2003). Similar developments focus on one directional traffic while most serious overtaking accidents happen on rural roads with opposing traffic. Later in 2007, BMW introduced a warning system of unsafe overtaking situations based on road infrastructure information (e.g., a hill, a sharp curve, sign information, etc.) (Loewenau et al., 2006). Hegeman et al. (2007) also proposed an OAS for two-lane rural roads that gives support on judging accepted overtaking opportunities based on the time gap to the next oncoming vehicle. This system was later tested in traffic simulation on two-lane roads, indicating improved traffic safety without negative consequences for traffic efficiency and driver comfort (Hegeman et al., 2009).

Despite that a large number of accidents are caused by human error or misbehavior, including cognitive (47%), judgement (40%) and operational errors (13%) (Ortiz, 2013), the inputs into current ADASs are mainly based only on the vehicle dynamic states and traffic context information without taking into account the driver factor itself. As vehicles are operating in a three-dimensional environment with continuous driver-vehicle-road interactions, allowing ADASs to monitor and understand diver behaviours in real-time and follow driver's intention is of importance to driver safety, vehicle drivability and traffic efficiency. Thus, the active interaction between the human driver and the intelligent units are the major object for the next-generation ADAS products (Tawari et al., 2014; Xing et al., 2018).

In general, research on the OASs includes the development of decision-making assistance on whether to initiate the overtaking (Fuchs, 2008; Saengpredeekom and Srinonchat, 2009) and the development for autonomous overtaking (Chiang et al., 2014; Milanesa, 2012). However, our research mainly concerns with the former which predicts dangerous overtaking manoeuvres that a driver is likely to perform in the next few seconds and alert the driver about these possible dangers, giving him enough time to react. Prediction of future human actions requires anticipation of future events from a limited temporal context, which differentiates it from action recognition where complete temporal context is available for anticipation (Wang et al., 2013). Previous works on general prediction usually deal with single-data modality (Kitani et al., 2012; Koppula and Saxena, 2013; Kuderer et al., 2012), but the driving environment is one kind of sensory-rich robotics settings and the way information from different sensors are fused largely affects the end performance of any prediction applications. Therefore, the machine learning techniques with a rich theory background rather than mathematic models can help deal with high dimensional real-time data of large volume. However, previous models learn representations using shallow architectures that cannot handle long temporal dependencies (Bengio and Delalleau, 2011). Basically, deep architectures with internal memory are required to handle long temporal dependencies (Hihi and Bengio, 1995) and allow the input features to undergo a hierarchy of non-linear transformation through its network to learn rich representations.

1.2 Research scope, objectives and questions

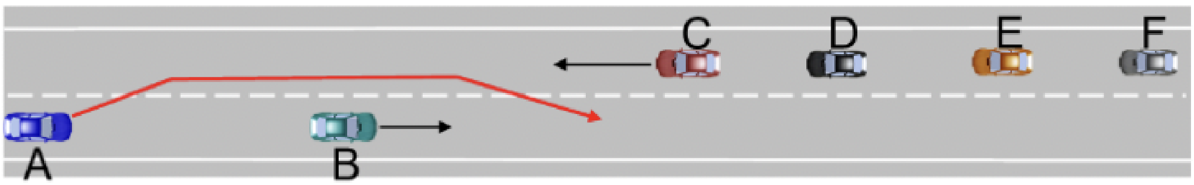
To better understand the problem and the scope of this thesis, this section indicates research aim, defines the scenario of interest and states the objectives and main research questions. The research aims to answer the question "*How to identify the driver intention to perform dangerous overtaking manoeuvres based on real-time sensor data*?".

Scope

The scope of this study is limited to overtaking manoeuvres performed on two-lane roads where the opposing traffic lane needs to be used during overtaking. The scenarios considered are illustrated in Figure 1.2. The ego/host vehicle A that performs the overtaking manoeuvre is defined as the overtaker, the preceding/lead vehicle B that is overtaken is defined as the overtaken vehicle, the oncoming traffic is varied from 0-4 vehicles (C – F) with variable distance and speeds. The ego vehicle is equipped with different types of sensors and the navigation system to collect real-time data about the driving context and the vehicle state.

There are four critical moments for one overtaking manoeuvre which are the intention triggering point (denoted as T_1), manoeuvre preparation point (T_2), lane crossing point (T_3) and manoeuvre finishing point (T_4). The specific moment when the driver arises an intention (T_1) is hardly detectable which can be the first moment of relative speed reduction between the ego vehicle and the lead vehicle, considered as the traffic context stimuli. At T_2, the driver uses the turn signal indicator, adjust speed and then turn the steering wheel. Finally, T_3 and T_4 are the moments that the vehicle just crosses the central line to start and finish the overtaking manoeuvre, respectively. Our research focuses on the time interval between T_2 and T_3 which is denoted as overtaking preparation before the vehicle departure from central lane markings. The temporal sequence up to 9s before the crossing of central markings is sufficient to cover the important features for our research purposes, which particularly comprises of 7s before and 2s after the moment of turning the steering wheel to the left for overtaking.

Figure 1. 2. The overtaking scenario



Objectives

The following research objectives are drawn up to address the aforementioned problem

- To understand the safety concerns related to the overtaking manoeuvre and the need of overtaking assistance systems
- To investigate the driver intention inference in the context of dangerous overtaking, taken into account multi-modal data from different sensors.
- To develop prediction models of dangerous overtaking based on Neural Networks in driving simulation as well as test this trained model in naturalistic driving, all with the assistance of MATLAB tools
- To evaluate the prediction performance of different types of Neural Networks used for deep-learning
- To discuss the relevance of the constructed model in real-world application

Research questions

1. How safe is an overtaking with respect to normal/accelerative overtaking and flying overtaking strategies?
2. How is the prediction performance between different neural network models?

3. Which are important indicators for driver intention inference of dangerous overtaking?

4. How is the prediction performance with respect to prediction time?

5. What is the feasibility of standardization of the prediction model for all drivers around the world?

1.3 Contents of research

This thesis is comprised of five chapters. Chapter 1 provides the introduction which includes the problem identification, the role of overtaking assistance systems, statements of research objectives and questions and the outline of the thesis. Chapter 2 focuses on the literature review on the concepts, characteristics and empirical facts of overtaking manoeuvres, the state-of-the-art developments of overtaking assistance systems and the driver intention inference studies. Chapter 3 focuses on methodologies used to identify dangerous overtaking, with respect to data collection methods, driver intention inference algorithms and workflow of model training process in MATLAB. The Chapter 4 presents the results found using MATLAB tools and following discussion. The Chapter 5 gives the conclusion on the research with implications, limitations and suggested the potential for future research.

Chapter 2: Literature review

2.1. Overtaking manoeuvres

2.1.1. Definition and types of overtaking manoeuvres

An overtaking manoeuvre is defined by "moving of the subject vehicle to another lane, passing of at least one (slower) preceding vehicle and moving back to the lane where the manoeuvre started" (Hegeman, 2008). Hegeman (2005) divided the overtaking task into 5 phases, including: 1. Decide whether to overtake, 2. Prepare to overtake, 3. Change lane, 4. Pass and 5. Return to own lane and each of these phases consists of several subtasks, making up to 20 subtasks (i.e. Some important subtasks are listed in Table 2.1). Yan et al. (2019) considered Hegeman's first two phases as "intention emerging process" and the rest of phases as "action executing process". Both Hegeman (2005) and Fei et al. (2019) agreed that the initial driver intention to overtake appears much earlier than the execution of the overtaking manoeuvre. The study of Farah et al. (2018) about overtaking the cyclist also showed that the decision on overtaking strategies was made when the drivers are further than 100m away from the cyclist (i.e., about 5s before reaching the cyclist). The presence of this large time window allows warnings and intervention systems to be effective to prevent a driver from performing a dangerous overtaking manoeuvre. Thus, this dissertation will focus on the first two phases mentioned mainly.

Table 2. 1. Phases and main subtasks of an overtaking manoeuvre

Phases	Subtasks
1. Decide whether to overtake	1.1. Verify overtaking wish/need 1.2. Verify whether overtaking is permissible (e.g., road signs, lane markings, …) 1.3. Verify an overtaking opportunity with respect to infrastructural factors (e.g., hills, curves, intersections, …)
2. Prepare to overtake	2.1. Judge the gap with the first oncoming vehicle 2.2. Observe any deviations of the preceding vehicle (e.g., left turn signalling, sudden deceleration, weaving, …) and other obstructing traffic from behind. 2.3. Maintain a proper following distance 2.4. Turn on indicator
3. Change lane	3.1. Steering, accelerating, monitoring
4. Pass	4.1. Continuation of acceleration, gear change 4.2. Monitoring the gap with oncoming vehicles 4.3. Pass the lead vehicle
5. Return to own lane	5.1. Turn off indicator 5.2. Steering, monitoring, accelerating/decelerating 5.3. Adjust speed

Source: Sumarized from the study of Hegeman (2008)

Earlier studies distinguished the overtaking strategies between accelerative (normal), flying and piggy backing types (Wilson and Besta, 1982).

- In accelerative overtaking manoeuvres, the overtaker approaches the preceding vehicle, adjusts his/her speed to follow the preceding vehicle, waits for a sufficiently large gap in the opposing traffic stream to overtake that vehicle.
- In flying type of overtaking, the overtaker drives at his/her desired speed and overtakes the preceding vehicle without car-following process.
- In piggy backing type of overtaking, the driver follows his/her preceding vehicle which is overtaking another slower vehicle in front.

In addition, other 2+ strategies of overtaking consider the driver overtakes more than one preceding vehicles at once, involving either accelerative, flying or piggy backing strategy (Hegeman, 2008). Also, according to another paper (Kashani et al., 2016), four overtaking levels are considered, including normal overtaking manoeuvre, aborted overtaking manoeuvre, lane sharing and cutting in type of overtaking manoeuvres. In general, accelerative overtaking manoeuvres are safer than flying overtaking manoeuvres as the drivers often drive at lower speeds and better control the interaction with the oncoming traffic (Dozza et al., 2016). Therefore, the accelerative strategy in overtaking is mostly used by the driver (Wilson & Besta, 1982; Hegeman et al., 2008) and this strategy can be divided into approaching, tailgating, lane changing, passing and lane returning. Farah et al. (2018) developed models that predict drivers' decisions to perform either a flying or an accelerative overtaking manoeuvre in the presence of oncoming traffic. They suggested that the subject vehicle speed was a good indicator of the driver's choice in overtaking strategies, in line with the findings of Bianchi et al. (2018) and Dozza et al. (2016). Bianchi et al. (2018) also found a significant correlation between the overtaking strategy and the nominal times to collision (TTC) in the study of cyclist-overtaking manoeuvres on a rural road: as the TTC decreases, more drivers used the accelerative strategy as slowing down and waiting for the oncoming vehicle to pass before accelerating to overtake the cyclist.

2.1.2. Overtaking rules and related traffic safety measures

Overtaking prohibitions

To solve the overtaking safety problem, structural overtaking prohibitions are applied in many countries. Different countries select locations for installing overtaking prohibitions for different reasons, such as limited sight distances due to curves and hills, level crossings/intersections or straight roads with perfect views which induce high driving speeds and driver distraction, … The Dutch Sustainable Safety Program of the Netherlands considers overtaking prohibitions as a possible means to increase safety of two- lane flow roads (CROW, 2002a; Wegman and Aarts, 2005).

Means of overtaking prohibitions can be a (double) continuous/solid centre line, accompanied with a road sign at the start of each road section as shown in Figure 2.1.a. Finland, New-Zealand and the USA use yellow paint (instead of white) for the (double) continuous centre line to indicate overtaking prohibitions. Other countries do use yellow paint for temporarily overtaking prohibitions, for example in case of road works. Although the double solid centre line can be replaced by physical barriers installed between the driving directions, the former is mostly preferred because they are cheaper to be implemented and more flexible to allow crossings in case of emergency. In a Dutch study, 20% of normally performed overtaking manoeuvres were still observed on sections with an overtaking prohibition despite of an overall overtaking frequency reduction due to overtaking prohibitions (Hegeman, 2004b). One possible explanation is that passenger car drivers who are allowed to drive at higher speeds up to 100km/h on these roads than drivers of trucks and cars with trailers (80 km/h), are more inclined to violate overtaking prohibitions. Koorey (2007) found that a lack of opportunities to overtake slow moving vehicles can cause frustration and even road rage among aggressive drivers, prompting dangerous overtaking manoeuvres and resulting in an increase in crashes, as traffic violations in general are positively correlated with accident involvement (Parker et al., 1995). Moreover, when the overtaking prohibition is in place, any violations to perform an overtaking manoeuvre become more dangerous situations as other drivers do not expect these overtaking manoeuvres (Houtenbos et al., 2005b). Davidse et al. (2002) also agreed with this finding and indicated that a road is safe when expected behaviour corresponds with real behaviour. This implies that overtaking is presumed to be more unsafe with the presence of overtaking prohibitions, all else being equal. To tackle overtaking prohibition violations, the European Transport Safety Council designated overtaking offences as one of the important areas of misconduct that needs traffic enforcement efforts in the future (ETSC, 1999). Police in Europe also targeted dangerous overtaking as the most important behavior that needs to be intervened to increase traffic safety (Makinen et al., 2003).

Overtaking lanes

Overtaking lanes are auxiliary traffic lanes alternating for the two driving directions, which are nearest the centre of the road and used for passing slower vehicles without confronting the oncoming traffic on the opposing lane. The concept of overtaking lanes to increase traffic efficiency and drivers' comfort is successfully applied in many countries, for example in Australia (Charlton et al., 2001, Charlton, 2007) and Sweden (Bergt et al., 2005). Figure 2.1.b demonstrates an example of overtaking lane in which short stretches of dual carriageway are used to enable overtaking opportunities and the driving directions are divided by means of a cable barrier. In the USA, alternating overtaking lanes and median barriers on multilane roads has been suggested to minimise the likelihood of head-on crashes with opposing traffic (NCHRP, 2003). May (1991) confirmed that well-designed overtaking lanes could significantly reduce the number of accidents caused by overtaking. In terms of efficiency, overtaking lanes may improve the capacity of the road from maximum 3600 pcu/h for two lanes to a maximum of 4000 pcu/h for the three driving lanes together (CROW, 2002a & 2002b), ultimately resulting in less aggressive driving behaviour as an indication of higher driver comfort (Shinar and Compton, 2004). Indeed, a Dutch study (Levelt and Rappange, 2000) indicated that more than half of the motorists feel irritated and make aggressive driving behaviours because of the delays caused by slow moving traffic in front. However, the overtaking lane in one direction requires overtaking prohibitions installed in the opposing direction lane with resultant disadvantages already mentioned above. Therefore, compared to the permitted overtaking case without overtaking lanes, the alternating overtaking lanes do not yield more overtaking manoeuvres in one direction (Harms, 2006). Kim and Elefteriadou (2007) also found no effect of overtaking lanes on capacity in their simulation study. In real world, any countries with narrow roads, high density of level crossings/intersections and short road segments, such as the Netherlands, cannot install overtaking lanes. The minimum design length of an overtaking lane is 1200 m (BTCE, 1997).

Driver assistance systems

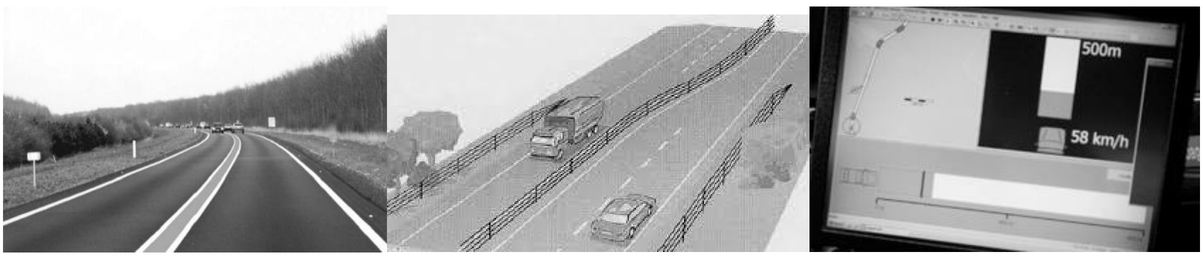
Driver assistance systems have been developed and improved for more than two decades. In 1994, high technology Intelligent Vehicle Highway System (IVHS) has paid a high attention to crash avoidance systems to tackle lane change/merge crashes (Wang and Knipling, 1994). Developments of overtaking assistants began in 2003 (Louwerse, 2003, Hegeman, 2004b). These assistants are supposed to warn drivers of unsafe manoevres by measuring the range and speed of the oncoming and preceding vehicle (Gray and Regan, 2005). In 2007, BMW introduced a so-called passive overtaking assistant on the market, which is based on the road infrastructure to warn drivers of unsafe overtaking situations (Loewenau et al., 2006). Its interface is displayed in Figure 2.1.c The advantage of driver assistance systems is helping drivers perform overtaking manoeuvres safely rather than preventing drivers from overtaking (i.e., overtaking prohibitions) or preventing conflicts with oncoming traffic (i.e., overtaking lanes). Therefore, overtaking safety can be guaranteed without causing negative capacity effects or discomfort. Also, driver assistance systems will work identically in any countries and road types and can be considered as a cheaper solution compared to other safety measures mentioned above. However, driver assistance may encourage overtaking manoeuvres and distracted drivers who are inclined to wholly trust the system can face extra risk as a result of other unexpected traffic situations.

International overtaking rules and executions

Various rules and regulations for road traffic and use of highway are set up by the “Ministry of Infrastructure and the Environment, Netherlands” (Road Traffic Signs and Regulations in the Netherlands), “Province of Alberta” (Use of highway and rules of the road regulation) and the “Government of UK” (The Highway Code) in which certain rules and regulations for the overtaking manoeuvre are considered under the subsection “Conditions for safe and legal overtaking” (Waterstaat, 2010; Alberta, 2002; UK Gov, 2017).

- Conditions before overtaking: It should be made sure that road markings and signage should permit overtaking, the road ahead is clearly seen (i.e., not when approaching bends, junctions, lay-bys, pedestrian crossings, hills or dips, …), the host vehicle is not being overtaken by its following vehicle and there is a sufficient gap between the host and lead vehicle (UK Gov, 2017)

Figure 2. 1. Solutions to reduce overtaking fatalities



Source: (Hegeman, 2008).
a. Overtaking prohibition; b. Overtaking lane and c. Overtaking assistance

- Conditions for safe and legal overtaking
    - The lead vehicle should be moving at a constant speed along a relatively straight route (Naranjo et al., 2008)
    - The left lane should be free or the approaching vehicle should be far enough to avoid collision (Perez et al., 2010)
    - The left lane must be long enough for the overtaking manoeuvre to be completed at the current speed (Naranjo et al., 2008)
    - The overtaking duration should be less than 15 seconds and the overtaken vehicle cannot increase its speed once the manoeuvre has been triggered (Milanes et al., 2012)
    - The host vehicle should depart to the left lane after a safe gap to the lead vehicle and return to the original lane after a sufficient gap created (Alberta, 2002)
    - The host vehicle must be able to accelerate enough to overtake the lead vehicle without violating the speed limit.
    - It should not follow the lead vehicle which overtakes another slower vehicle ahead because there may only be enough room for one vehicle (UK Gov, 2017)

Hegeman (2005) also studied the international differences and similarities in overtaking rules and executions on two-lane rural road. Speed limits on the prohibited overtaking roads generally vary between 80 and 100 km/h with lower limits for (large) trucks, the lowest being 70 km/h in Sweden and Italy. In the Netherlands, the "Sustainable Safety Program", launched in 1992, includes overtaking prohibitions on all two-lane rural roads introduced in the self-explaining road concept with a speed limit of 80 km/h (distributor roads) and 100 km/h (flow roads) (Wegman and Aarts, 2005). In the study of Hegeman (2005), the most cited reason for installing overtaking prohibitions is restricted views. Sight distance can be defined as the visible roadway that can be observed by the drivers (AASHTO, 2001) and the passing sight distance is an essential aspect of single carriageway road section which allows drivers to judge whether the overtaking vehicle can safely complete the entire passing manoeuvre. Other reasons are bad surface, temporary high traffic flows, bad weather, near bus stops (i.e., Austria) or inside the tunnels (i.e., Italy). However, compliance to overtaking prohibitions that are installed only for safety reasons is estimated to be low in all countries because of the small perceived chance by drivers of getting caught by police. Besides fixed fines, Finland applies income-dependent fines and the USA, UK and Sweden offenders receive a notification on driving license with the risk to lose their driving license.

In terms of indicator usage, the rules are fairly similar in most of the countries which require the use of indicator at the start and end of the overtaking manoeuvre, right before changing lane to the opposing traffic lane and then to the original traffic lane respectively. However, the indicator usage in practice may reach only 64% in the study of Hegeman (2005) and 44% in the study of Lee et al. (2004). Apart from the indicator, the start of an overtaking manoeuvre can also be indicated by means of other signs such as headlight flashing as done in Finland, Spain, Italy, Brazil, … With respect to safe headway keeping, the two-second rule (i.e., keep at least 2s headway with preceding vehicles) is known in Belgium, Finland, the Netherlands, New Zealand and Austria. However, Hegeman (2005) found that more than half of the observed headways were smaller than 1s. She also indicated other overtaking executions seen in the real world which are three vehicles side by side on two traffic lanes, the preceding and oncoming vehicles slowing down to assist the overtaker, the preceding vehicle moving to the emergency lane, involved vehicles taking invasive actions due to misjudgements of the overtaker, the overtaker cutting in in front of the overtaken vehicle, …

2.1.3. Empirical facts of overtaking behaviour observations

Early studies on overtaking manoeuvre were developed by the American, Swedish and Australian. Much research effort in overtaking observations was made during the 1930s, then again, the interest in overtaking behaviour has grown again during the 1980s and at the start of the 21st century (Jenkins, 2004). Matson and Forbes (1938) were the pioneers who used moving observation vehicle technique with visual recording methods to study the driver overtaking behaviour. Other researchers who also used instrumental vehicles to conduct overtaking observation studies are Lerner et al. (2000), Hegeman (2005), … Other methods of collecting overtaking behaviour data including simulator study, accident analysis and test track observation (i.e., a test using still video camera which is situated on a higher ground level to observe the whole area of overtaking section) (Hegeman et al., 2005; Hassan, 2005; Gera and Shinar, 2005; Benedetto et al., 2004).

Accepted gap

Accepted gap can be measured as the estimated minimum time available for safe overtaking manoeuvre before the arrival of the next oncoming traffic or the certain threshold of distance gap between the ego vehicle and the next oncoming vehicle at which an overtaking opportunity can be accepted. Wilson and Best (1982) indicated that 14% of accepted gaps were judged to be too small (threshold 400m). Gordon and Mart (1968) claimed that drivers are unable to estimate the overtaking distances and safety margins correctly because the speed of the involved vehicles, especially the overtaken vehicle is not easily anticipated. Thus, accepted gap is one of the most considered indicators in overtaking, for which 11.5s was found by both Crawford (1963) and Tapio (2003). Van der Horst et al. (1993) suggested that the observed overtaking average duration of 7.8s should be added with a safety margin of 4s to set the threshold of safe time gap for positive advice (i.e., "It's safe to overtake"). Hegeman et al. (2005a) also found similar results that the average overtaking duration found of 7.8s (SD=1.9s) which is independent of overtaking strategy and of the observed overtaken vehicle's speed, should be added with a safety margin of 3s to achieve the overtaking assistant threshold.

Miller and Pretty (1968) assumed that every driver has a critical gap which represents his boundary between acceptance and non-acceptance of a presented gap. A time to collision (TTC) below 3s has been found to be experienced as uncomfortable by drivers (Hoogendoorn, 2000). Godfrey et al. (2016) also used the TTC as a surrogate safety measure of the risk associated with passing manoeuvres and found that TTC less than 3 seconds caused unsafe passing manoeuvres involving sudden speed reduction, flashing headlights, and lateral shift to shoulders. Lee et al. (2004) studied naturalistic lane-changes and suggested a TTC of between 4s and 6s.

Other values of accepted gap may vary between 9.0s and 12.4s for different oncoming vehicle types and different lane width while the overtaking duration values of 6.5s, 6.7s, 11.2s and 13s were also found in literature (Hegeman, 2008). Differences between these findings can be explained by differences in definitions of the start and end of the manoeuvre. Hegeman et al. (2007) developed the overtaking assistant to support drivers in overtaking decision-making based on accepted time gap with the minimum assistant threshold setting in the driving simulator of 8s. The advice of the overtaking assistant is likely to be less respected by the drivers as the longer the assistant threshold. Thus, the time to carry out the overtaking manoeuvre must be less than 15s as stated by Milanés et al. (2012) and 15s was also chosen as the maximum time to perform quality overtaking manoeuvres in the study of developing test protocol for the highway overtaking manoeuvre (Kakade, 2018). According to Greenshields et al. (1935), the minimum overtaking distance requirement was between 305 and 488 m. The mean overtaking distance was 282 m (SD = 75 m) in the study of Harwood and Sun (2008) and 175.5 m (SD = 56.3 m) in the study of Farah (2016).

Headway at the start of an overtaking manoeuvre

Hegeman (2008) observed 48 overtaking manoeuvres while driving at 70, 80 and 90 km/h using an instrumented vehicle and found that the mean observed distance headways between the host and lead vehicle were 17.8m (SD = 9.8m) at the start of overtaking manoeuvre. Flying overtaking and piggy backing are suggested to have longer headways compared to accelerative/normal overtaking manoeuvres. Farah (2016) suggested the mean following gap at the moment of initiating overtaking was 25m. Other studies found the headway distance between the ego and lead vehicle of 1s (SD=0.5s) (Roozenburg and Nicholson, 2000) and 1.6s (SD=1.3s) (Farah, 2013). Larger headways at the start of the manoeuvre will increase the overtaking duration, thereby possibly increasing the risk of a collision, especially with unseen oncoming traffic or unexpected movements of overtaken vehicle. According to Hegeman (2008), headways smaller than 1s at the start of overtaking manoeuvres are likely to be less dangerous than during normal following conditions but the driver have to either switch off or adjust the ACC to smaller headways. The minimum headway time should be greater than 0.8s as per the ISO 15622 standard for ACC (ISO, 2010)

Acceleration

Shinar (1998) believed that acceleration and speed of overtaking vehicle is a function of the speed of the overtaken vehicle and for various levels of constraint on the overtaking manoeuvre. Roozenburg and Nicholson (2000) carried out Monte Carlo simulations of their developed overtaking model with the mean acceleration of $\pm 3.6\ \mathrm{m/s^2}$ $(\mathrm{SD} = 0.45\,\mathrm{m/s^2})$. Khodayari et al. (2012) developed an intelligent control system for autonomous overtaking in which the maximum acceleration was limited to $\pm 3.5\ \mathrm{m/s^2}$. Taken into account the comfort aspects for drivers, Hrishikeh (2018) agreed on the maximum longitudinal acceleration of $\pm 3.5\ \mathrm{m/s^2}$ to be used in developing test protocol for the highway overtaking manoeuvre. Generally, the maximum acceleration in other studies varies such as $\pm 2.5\ \mathrm{m/s^2}$ (Schmidt, 2017), $\pm 5\ \mathrm{m/s^2}$ (Gustafsson, 2013) and $\pm 7\ \mathrm{m/s^2}$ (Chandru and Selvaraj, 2016). As per the ISO standard 15622 (ACC), the average automatic deceleration of ACC systems shall not exceed 3.5 $\mathrm{m/s^2}$, the average rate of change of automatic deceleration (negative jerk) shall not exceed 2.5 $\mathrm{m/s^3}$and automatic acceleration of ACC systems shall not exceed 2 $\mathrm{m/s^2}$ (ISO, 2010).

Relative speed

The threshold speed difference to provoke an overtaking wish for the ego vehicle varies between 5 and 40 km/h, as revealed by a survey amongst drivers in 17 countries (Hegeman, 2008). The relative speed range of 5-40 km/h was also used in the study of Hrishikeh (2018). AASHTO (American Association of State Highway and Transportation Officials) design criteria are based on the assumption that the speed differential between the host and lead vehicles is equal to 16 km/h, while this value is closer to 19 km/h as found by Harwood and Sun (2008) and 26.9 km/h [SD = 6.78 km/h] suggested by Roozenburg and Nicholson (2000). Bar-Gera and Shinar (2005) assessed the speed differential threshold - if there is one -at which drivers decide to overtake a lead vehicle and found that the more variable the driver's speed the more likely he or she was to pass the vehicle ahead even when the overtaken vehicle's speed was greater than traffic flow's average speed. Also, the host vehicle mean speed was 75.6 km/h during overtaking (SD = 21.2 km/h) (Farah, 2016), the host vehicle speed range was 80-96 km/h when changing lanes (Chen et al., 2015) and almost no drivers initiate lane change at vehicle speeds above 129 km/h (Chen, 2016).

Effect of changes in variables

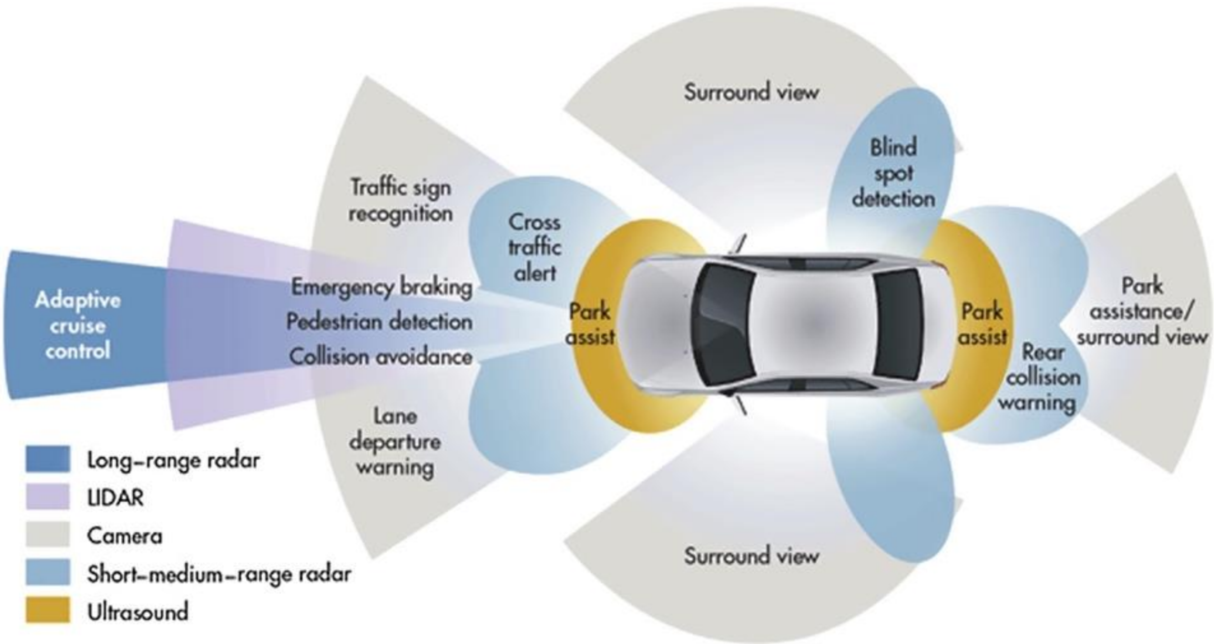
It is found that when drivers have the larger available gaps, the overtaking manoeuvre was performed in a more relaxed manner with increased overtaking duration and distance (Farah, 2013). Also, the overtaking duration significantly decreases with higher driving speeds of the ego vehicle at the beginning of the manoeuvre. Drivers are likely to keep small headways before overtaking to minimize time spent in the opposite lane (Ahmad and Papelis, 2000). Vlahogianni (2013) concluded that the overtaking duration depends the speed difference, the speed of opposing traffic, the gender as well as the types of overtaking manoeuvre. It is observed that overtaking chance increases significantly with the absence of any hindrance to overtake, the decreased longitudinal distance and the decrease of relative speed (Budhkar and Maurya, 2016). Farah (2016) concluded that the probabilities to complete the overtaking manoeuvres increase with shorter following gaps between the ego and lead vehicle at the moment of initiating the manoeuvre, larger accepted overtaking gaps, higher desired driving speeds and slower speeds of the front vehicles.

2.2. Advanced driver assistance systems

2.2.1. Advanced driver assistance systems in general

An Advanced Driver Assistance System (ADAS) is designed to allow the driver to perform manoeuvres on roads with less stress, more safely, more comfortably, and efficiently (Masikos et al., 2013). Compared to in-vehicle passive safety systems (e.g., airbags, seat belts, …) which minimise the injuries for drivers and passengers in cases of accidents, ADASs are active safety features designed to prevent accidents from happening by alerting the driver to potential problems, helping reduce the workload of driving or even automatically taking over the control of vehicle's steering and throttle in case of an emergency situation to avoid collision. ADAS can be grouped according to three driving phases, including environment detection (recognition), decision making (judgment) and implementation of the action (operation) (Hiramatsu, 2010). ADASs as modern safety systems have one of the fastest development rates in the field of automatic vehicles and autonomous driving. ADAS relies on a holistic system based on multimodal sensors such as light detection and ranging (lidar), radar, camera, and GPS as illustrated in Figure 2.2.

Figure 2. 2. Distribution of ADASs in an advanced vehicle with lidar, light detection and ranging



Source: Yang et al. (2020)

In the last decade, a great variety of ADAS systems have been tested by automotive manufacturers with successful deployment in commercial vehicles, as listed as bellows:

- **Adaptive cruise control (ACC)** is designed to support drivers in maintaining a safe distance to the lead vehicle by brake interventions and vehicle acceleration/deceleration after the detection of changes in lead vehicle's speed. The study of Bar-Gera and Shinar (2005) suggested that the tendency to overtake vehicles in unnecessary and undesirable cases may be reduced with the introduction of in-vehicle ACC. Also, **Forward collision warning systems (FCW**) paired with ACC are active safety features that warn the drivers in the event of an imminent frontal collision by making use of a scanning device mounted at the front of vehicle to measure the distances from front vehicles.

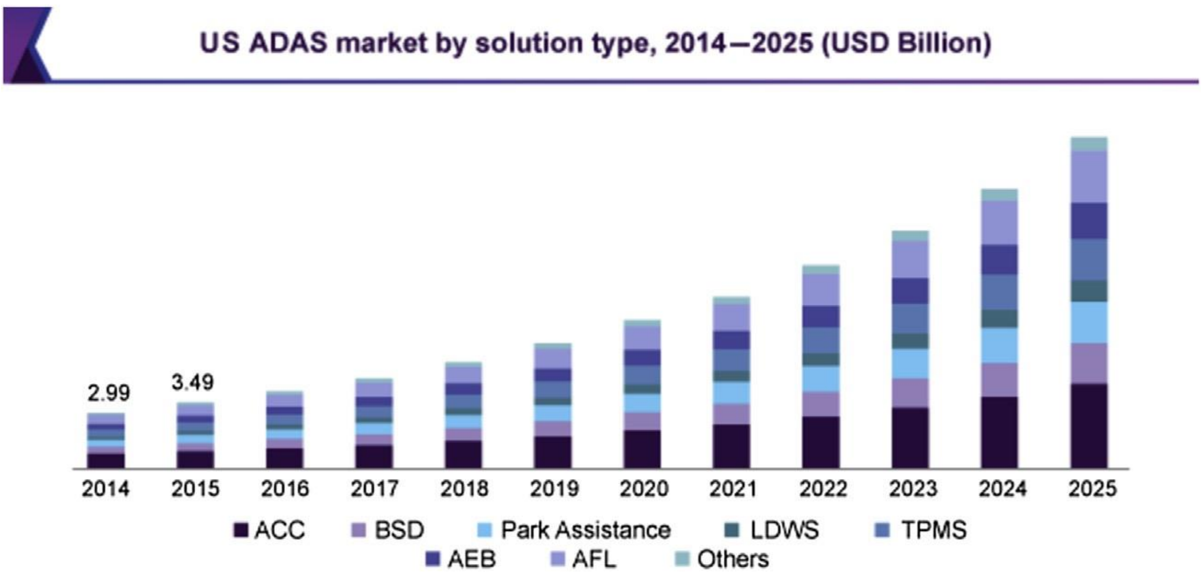
- Lane departure warning (LDW) is an advanced safety technology installed in vehicle to alert drivers via auditory warning, visual warning and hepatic feedback when they unintentionally drift out of current lanes without a turn signal. In addition, **Lane keeping assistance** is coupled with LDW to actively assists the driver to remain in the marked lane by influencing the lateral movement of vehicle. These systems may use a camera to detect lane markings and monitor the vehicle's position in relation to the lanes or the infrared system can be mounted under the front bumper to detect the lane mark crossings on the road based on different reflections from the signals. **Lane change Assist System** alerts the driver about the presence of approaching vehicles in the adjacent zones from the rear. A radar sensor on each side of the rear of the car scans the surrounding area and detects any vehicle near and behind the vehicle. Other kinds of sensors are also used in LCAS such as camera, infrared and ultrasonic sensors. However, if the lane marks are not clear or the weather condition is adverse such as rainy, foggy and ice on the carriageway, these systems cannot work well. Also, these systems will fail to work if the drivers do not use the turn signal. In fact, based on the

US traffic statistics, less than half of the drivers signal when they change the lane during their normal driving (Yang et al., 2020).

- **Intelligent speed adaption** is an in-vehicle system that supports drivers' compliance with the speed limit in force at a particular location. GPS allied to digital speed limit maps allows ISA technology to continuously update in-vehicle speed limits in accordance with statutory local speed limits. Jamson et al. (2010) also investigated how mandatory and voluntary ISA might affect a driver's overtaking decisions with respect to the frequency and safety of the manoeuvres on rural roads by presenting drivers with a variety of overtaking scenarios. However, they found that drivers disengaged the voluntary ISA in 70% of overtaking scenarios while the mandatory ISA could affect the safety of overtaking manoeuvres.

- **Electronic Stability Control** designed to automatically provide traction and anti-skid support in cases of loss of control realized by a yaw sensor, wheel speed sensors and a steering angle sensor. **Emergency Brake Assist** works in combination with **Anti-lock Braking Systems** to make use of wheel speed sensors to help braking as effective as possible in critical situations while avoiding wheel lockage during an episode of heavy braking.

Figure 2. 3. Advanced Driver Assistance Systems market prediction



Source: Grand View Research, Inc.

(ACC, adaptive cruise control; AEB, automatic emergency braking; AFL, adaptive front light; BSD, blind spot detection; LDWS, lane departure warning systems; TPMS, tire pressure monitoring system)

Other common ADASs are pedestrian detection, traffic sign recognition, blind spot detection,… Besides inputs from various sensors present inside or outside the car or with the help of a vision-based camera, additional inputs can be sourced separately from other vehicles (i.e., Vehicle-to-Vehicle (V2V)) or Vehicle-to-Infrastructure systems (i.e., mobile telephony or WIFI data network). However, ADAS is currently only used for assisting and helping functions, leaving final decision making to the car driver who has the ability to override the electronic assistance in all conditions and is legally responsible for his driving. It is also predicted by many automotive market analysers such as Grand View Research that ADAS products will show a significant increase in the next 5 years (Figure 2.3).

2.2.2. Overtaking assistance system

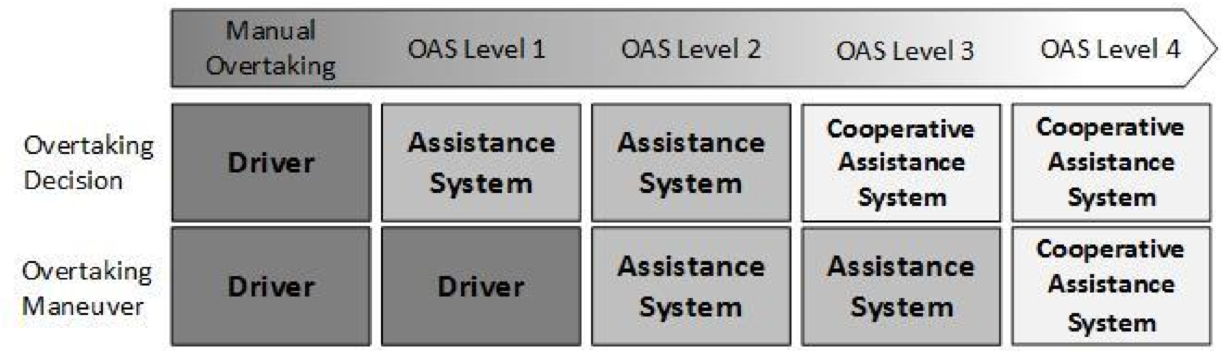
Overtaking is still one of the difficult manoeuvres where driver needs to be assisted the most with the help of ADAS application. The Overtaking Assistance System (OAS) is a subsystem of the ADAS and designed to assist the driver in the overtaking process. Although ADAS listed above may not be incompatible with overtaking and must be automatically deactivated when the driver initiates overtaking manoeuvre, many of its components can be very useful, taking into account the capabilities offered by the radar sensors to measure speeds and distances of all vehicles involved. For example, Lee et al. (2004) confirmed that an overtaking assistant should include a collision warning system if other vehicles approach too close. The reuse of already existing ADAS functionalities would encourage the user acceptance of new models.

State-of-the-art OAS developments

In general, research on the OAS includes the developments of decision-making assistance as well as autonomous overtaking technologies. The former can be seen in the development of the ''Dynamic Pass Prediction" system which informs drivers whether it is safe to overtake on road sections of two-directional traffic based on navigation system data such as curve and sign information (Loewenau et al., 2006).In 2007, this so-called passive overtaking assistant was introduced by BMW on the market. Another example is the work of Hegeman et al. (2007) who proposed an overtaking assistance system for two-lane rural roads that gives support on judging accepted overtaking opportunities based on the time gap to the next oncoming vehicle. This system was later tested in traffic simulation on two-lane roads, indicating improved traffic safety without negative consequences for traffic efficiency and driver comfort (Hegeman et al., 2009). Gong et al. (2016) used various sensors for environmental perception, GPS receiver for self-location and V2X communication for interaction information (i.e., distance, velocity) while developing decision-making model for overtaking behaviour on freeways. This developed model was integrated into their vehicle "Ray" in the simulation environment with experimental results showing the feasibility and reliability of the model. Fuchs (2008) studied a constraint-based and context-aware overtaking assistance system with fuzzy-probabilistic risk classification to support decision-making for initiating overtaking manoeuvre. Also, Saengpredeekorn (2009) proposed a new technique to define the overtaking distance using image process to assist decision-making process.). The latter area of research includes, for example, the study of Chiang et al. (2014) which proposed an embedded driver-assistance system using multiple sensors for a safe overtaking manoeuvre; the work of Vicente et al. (2012) which suggested an intelligent automatic overtaking system using vision for vehicle detection. From another perspective, Wasudeo (2015) reviewed on OAS and classified them into three categories based on technology used. Firstly, OAS proposed by Rafael et al. (2009) is the system to estimate overtaking risk, consisting of Vehicle-to-Vehicle (V2V) Communication to share vehicle kinematics information and road shape between vehicles over the 3G cellular network, the Global Navigation Satellite System (GNSS) combined with dead-rocking sensors and digital maps to predict lane change and collision and the Collision Avoidance System. Human-machine Interface (HMI) is also used to make the driver aware of dangerous situations for overtaking. Secondly, OAS in the study of Antonio et al.

(2013) instead used another technology called VANET (Vehicle Ad hoc Network) as the medium of communication to share kinematics information. This VANET system is based on coordinate position message broadcast protocol which interacts with other vehicles using wireless sensors, works irrespective of any infrastructure and position vehicles in relatively long distance away from the ego vehicle to assist the driver while performing the overtaking manoeuvre. Finally, Jarnea et al. (2015) proposed an approach which is not based on V2V communication but rather the acquisition of real-time scenario operations. This technique uses stereo vision cameras and radars which capture the real time images of the front and back side of the vehicle, obtain the distances between the objects and calculate the disparity map measures to inform and assist the driver to perform overtaking manoeuvres. Figure 2.4 illustrated the transition between different levels of the OAS in which the cooperative assistance system means some assistance systems in different vehicles can work together by means of communication (e.g., V2V, VANET, …). The study of Hegeman et al. (2009) showed that the assistance in judgement of the distance gap with the first opposing vehicle can be difficult because no radar, laser, camera or sensor can be able to detect far enough ahead unless means of navigation systems based on V2V communication are available. However, the European project PReVENT aims to develop a model which warns drivers about approaching vehicles with a relative velocity of 120 km/h from long distance by using sensors (PreVENT, 2005).

Figure 2. 4. Transition between different levels of overtaking assistance system



Source: Basjaruddin et al. (2014)

Monitoring system architecture in OAS

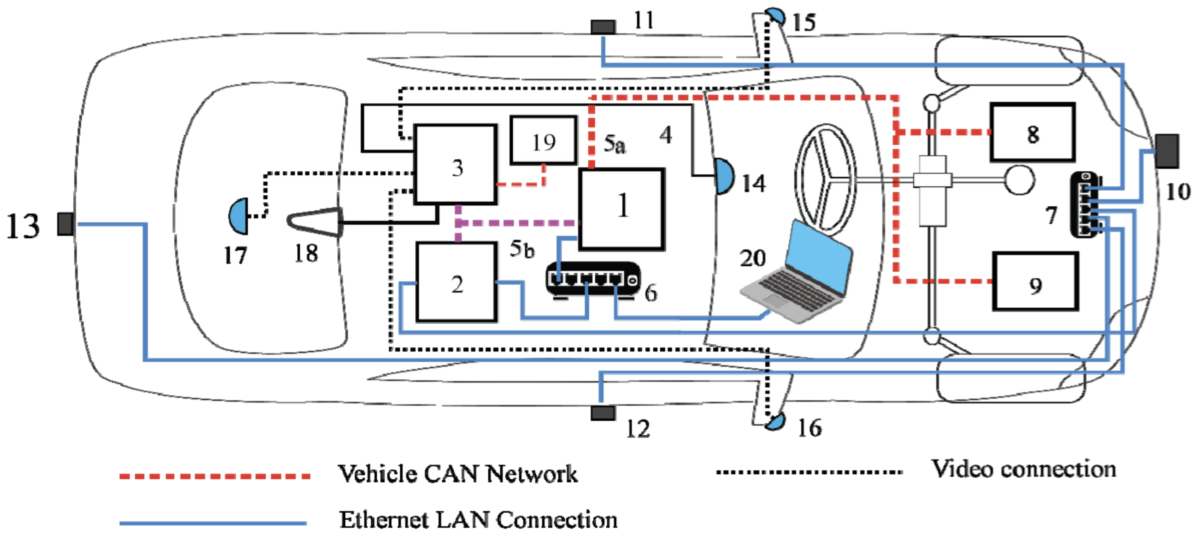
Zamfir et al. (2020) illustrated an ideal monitoring system architecture of the overtaking manoeuvre via a series of sensors and its own communication network, which operates independently from other ADAS devices already installed in the vehicle. Figure 2.5 describes the system as follows:

- Module 1 is responsible to detect the road configuration and recognize the overtaking manoeuvre initiated by the driver. The main parameters monitored are the steering wheel angle, the acceleration and brake pedal angles, the longitudinal and lateral acceleration, … However, most of the dynamic vehicle parameters required for overtaking manoeuvre analysis can be practically taken from the Electronic Stability Program (ESP) system via the propulsion-associated CAN 5b network. GPS precise position monitoring and the inclusion of information related to lane number, road category, radius of curvature, road slope … in digital maps are mandatory and useful to increase traffic safety.

- Module 2 is responsible for the real-time monitoring of the front and rear areas of the vehicle at 360 degrees surrounding area, simultaneously receiving information from the four sensors via an Ethernet switch 7. Useful radar sensor ranges suggested for overtaking monitoring are 300-350m for the front radar, 100-150m for the rear sensor and 25-60m for the two side radars. The radar sensor measures the distance, relative velocity and angular orientation of any objects which reflects waves transmitted by the transceiver to the receiver.

- Module 3 performs recognition functions of those objects identified in parallel by radar sensors controlled by previous Module 2. The most important function consists of image acquisition from video cameras and graphical image processing based on the theory of neural networks defined and trained to recognize the classes of objects (e.g., vehicle types, traffic signs, …)

Figure 2. 5. System architecture of the overtaking manoeuvre monitoring system



Source: Zamfir et al. (2020)

1.Master module; 2. Radar control module; 3. Video, GPS and IMU control module; 4. Overtaking Manoeuvre Monitoring System (OMMS); 5. CAN network (5a. Vehicle internal CAN; 5b. ODAS CAN-FD Network); 6-7. Ethernet switches; 8. EPS (Electronic Power Steering) – ECU; 9. Electronic Stability Program (ESP) – ECU; 10-13. FMCW radar sensors placed in front, sides and rear locations on the vehicle; 14-17. High resolution video cameras placed in front, sides and rear locations on the vehicle; 18. GPS – antenna; 19. Inertial Measuring Unit (IMU) 9 DOF

Graphic information processed in Module 3 about recognized objects found in surrounding area are passed to Module 1. Once the overtaking manoeuvre is recognized by Module 1, a command is sent to Module 2 to strictly store information of vehicles involving in the overtaking manoeuvre (i.e., the vehicle in front or appearing on the opposite front lane, …).

The information can also be validated by processing GPS data and positioning the vehicle on an electronic map.

Future improvements in OAS

The abovementioned monitoring system architecture lacks of the monitoring component of the driver behaviour and the inputs of current ADASs are mainly based only on the vehicle dynamic states and traffic context information without taking into account the most critical factor, the driver itself. Meanwhile, a large number of accidents are caused by human error or misbehavior, including cognitive (47%), judgement (40%) and operational errors (13%) (Ortiz, 2013). The important challenges of ADASs and vehicle automation are concerned with not only the adaption to different traffic situations but also the cooperative participation with the human drivers as "team-players" (Christoffersen and Woods, 2002). The active interaction between the human driver and the intelligent units are the major object for the next-generation ADAS products (Tawari et al., 2014; Xing et al., 2018). Although the autopilot products of Tesla are one of the most successful commercial driver assistances and semi-automated ADAS in the world, Tesla car was also reported for car crashes worldwide (The Guardian, 2018). One of the most common reasons for such a crash is the driver over-trusting the autopilot with activated systems while there is a lack of mutual understanding between the driver and the automation. Therefore, the driver's intention needs to be recognized and corrected by future effective ADASs, as of importance to driver safety, vehicle drivability and traffic efficiency. For example, driver intention inference technique allows ADAS to warn potentially dangerous situation as early as possible before any vehicle movements realized by intention; better assess the future risk based on the driver's driving styles (Berndt and Dietmayer, 2009) or avoid making decisions against the driver's intent especially in case of the level 3 or higher automated vehicle (according to the SAE International standard on the classification of automated vehicles) which requires a smooth and safe transition of control authority between the driver and the autonomous controllers (Eriksson and Stanton, 2017; Nilsson and Falcone, 2015). In the end, developments in driver intention inference can accelerate a more naturalistic human-like on-board decision-making system for future autonomous vehicles (Liu and Pentland, 1997). Noticeably, because the driver can be distracted from the driving task by an increasing use of in-vehicle devices and information systems, it is suggested that the design of future ADAS should integrate intended driver behaviours from the early design stages (McCall, 2006a&2006b). The topic of driver intention inference will be further discussed in the next part.

2.3. Driver intention inference

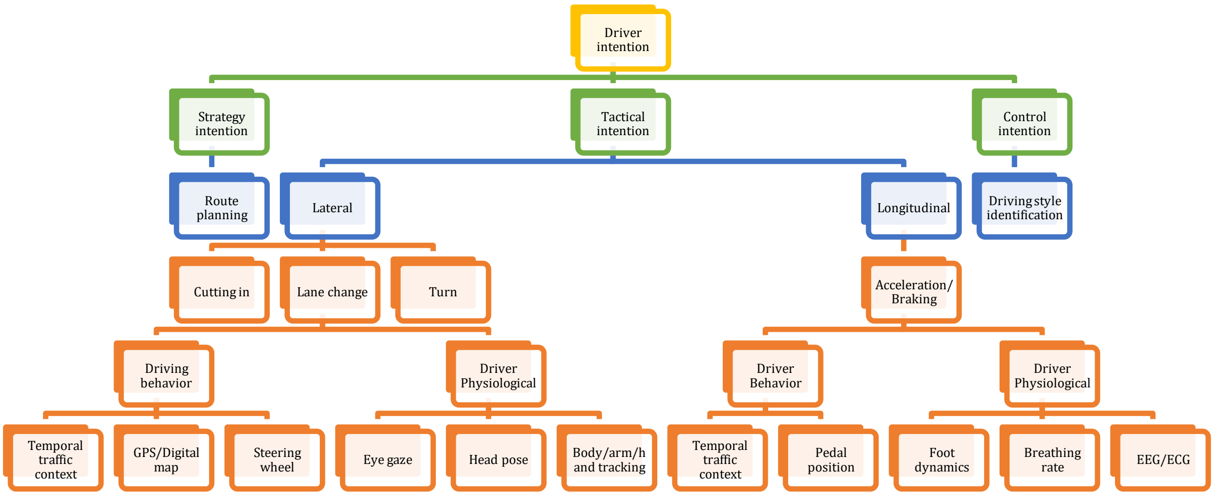
2.3.1. Driver intention mechanisms

The human intention has been theoretically studied in the past two decades. Intention refers to the thoughts that the driver has before performing the actions based on the cognitive psychology perspective (Carruthers, 2007). The theory of planned behaviour postulates that intention (i.e., supportive expression towards behaviours under study) is the most proximal determinant of behaviour and is determined by three conceptually independent variables: (1) Attitude towards behaviour, (2) Subjective norm reflecting pressure from social life of human, and (3) perceived behavioural control as confidence of an individual to perform the behaviour (Ajzen, 1991). The process of understanding the intention of another agent based on its actions is called intention recognition (Tahboub, 2006). For designing adaptive automation that can support human's decision-making, driver intention recognition is of importance although human intentions may not result in observable behaviors which can be described as "intention-action gap" (Howard & Cambria, 2013). Driver intention can be classified into different categories according either the motivation, timescale or direction of driving, with the last two categories as the two most straightforward ways of classification.

- **Timescale-based driver intention classification:** Michon (1985) suggested that driving skills of the road user can be classified into three levels: strategy, tactical and control levels. Strategy level defines planning skills such as trip route, destination, comfort zone and risk assessment, which requires time constants of at least several minutes. In terms of tactical level with time constants in seconds, the driver will make a short-term decision such as turning, lane changing and braking manoeuvres and perform a sequence of operational actions on vehicle to negotiate the prevailing circumstance. Meanwhile, the control intention occurs within the shortest time constant in milliseconds and stands for the willing of the driver to stay safe and comfortable in the traffic situation. Another driver model, namely, Adaptive Control of Thought-Rational cognitive architecture (Salvucci, 2006) shares similarities with the three-level architecture of road user model given by Michon. He developed the integrated driver model into three main components, which are control, monitoring and decision-making modules. The control component is considered as the same as the control level given by Michon, responsible for perceiving the external world and transferring the perceptual signals directly to the vehicle. The monitoring component maintains the awareness of the current situation while the decision-making component functions as part of Michon's tactical level.
- **Direction-based driver intention classification:** There are two basic directions for the underground vehicle, which are the longitudinal and lateral intention. The driver's longitudinal behaviour includes braking, acceleration, lane keeping, … Lateral behaviours mainly include turning, lane changing and merging. There are many studies on driver deceleration/braking intention prediction (Takahashi & Kuroda, 1996; Tran et al., 2012; Kumagai et al., 2003), and lane change intention prediction (Campbell (2015); Lethaus et al. (2011); Hou et al. (2011)). However, it is less accurate to describe the intention as merely longitudinal or lateral as the complex driving manoeuvre comprises of multiple short-stage actions.
- **Task-based driver intention classification:** The multitask-based intention usually contains both longitudinal and lateral manoeuvres compared with the single-task oriented intention. Liu and Pentland (1997) analysed the patterns within a driving action sequence. Imamura (2010) developed a driver intention identification and labelling based on the assumption of compliance with traffic rules.

Figure 2.6 illustrates the taxonomy of driver intention systems, also suggesting sources of data which can be used to infer the driver intentions.

Figure 2. 6. Taxonomy of driver intention systems



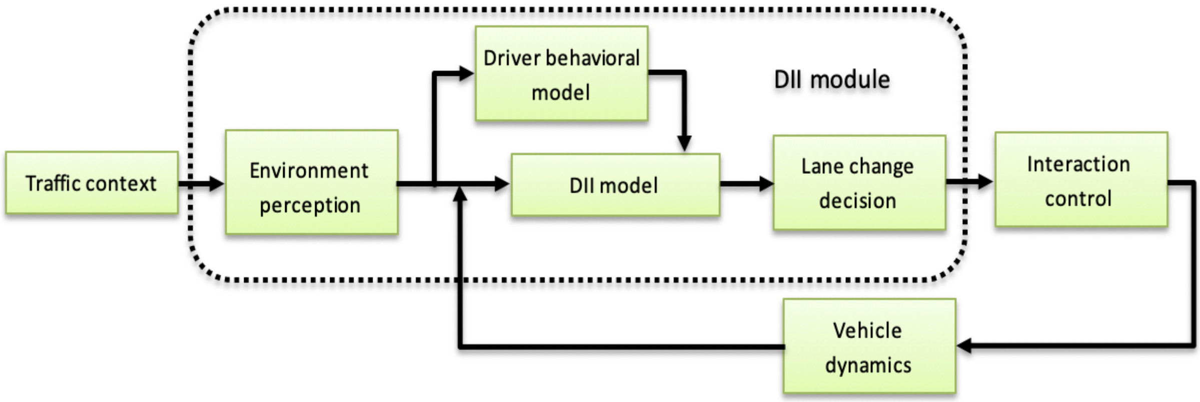
Source: Adapted from Yang et al. (2020) (ECG = Electrocardiography; EEG = Electroencephalography)

2.3.2. The architecture of driver intention inference system

Because lane change can be considered as the first observable action of overtaking manoeuvres, previous literature on lane change intention inference can help recognize the overtaking intention. Driver intention inference (DII) system mainly contains the following modules: road and traffic perception module, vehicle dynamic measurement module, driver behaviour recognition module and DII module, as depicted in the Figure 2.7. Road and traffic perception module detects the surrounding traffic situation, using cameras, light detection and ranging (lidar), radar and GPS signals. Meanwhile, relative distance and velocity between the ego vehicle and the preceding vehicle can be obtained through the Controller Area Network (CAN) bus. These traffic and vehicle data together with the driver behaviour signals (i.e., from the driver head rotation, eye gaze, body movement, etc) will be fed into the DII module. The probability of lane change intention is then calculated by the DII module based on the fused information. The lane change decision is based on a binary signal produced. As the decision is activated, the interaction control module monitors driver dynamics (e.g., EEG, eye gaze behaviours, head/body movements, etc.) and the driver vehicle interface (e.g., hand/steering interaction, foot/brake & acceleration, etc.). The vehicle dynamics data (e.g., yaw angle, longitudinal and lateral velocity, path and position, etc.) ultimately feeds back as the continuous input into the DII module.

The DII system can clearly define the time flow of the driver intention procedure. At the strategy level, the driver first perceives the traffic context, then generate the intention and performs a series of checking behaviours to assess the safety of the surrounding traffic. Once the safety opportunity is given, the driver will decide to activate the intended manoeuvre at the tactical level. Next, the driver controls the vehicle through the steering wheel and the pedal at the control level. Finally, the vehicle responds to control behaviours and vehicle dynamic changes.

Figure 2. 7. DII framework of lane change



Source: Adapted from Yang et al. (2020)

2.3.3. Inputs for driver intention inference system

Generally, indicators for driver intention recognition found in literature (Doshi and Trivedi, 2011; Lefevre et al., 2014) can be classified into information about the vehicle state, the driver itself and the situational context. The signals from three parts of the traffic-driver-vehicle loop can be used as inputs into the DII system. While the understanding of specific traffic context perceived by the driver helps reasonably infer driver's intention, the driver behaviour information enables the estimates of how long the driver has generated the intention and how the driver performs a series of safety checking on surrounding traffic. Meanwhile, the vehicle dynamics signals indicate the driver's actions taken to realize the intent. Table 2.2 summarizes the common input signals and sensors as multimodal signals used to infer driver mental intent and predict driver behaviour. Selecting the most important and relevant data as input into the DII system can increase the accuracy of the prediction rate and reduce the false alarm rate.

Table 2. 2. Common input signals and sensors used for driver intention inference

Sensor sources	Sensor categories
Traffic	Current ego-vehicle position (collected with GPS and digital map), relative distance, velocity and acceleration with respect to the front and surrounding vehicles (collected with cameras, radar, light detection and ranging/lidar)
Driver	Cameras (head rotation, gaze direction, foot dynamics). EEG, EMG, heart rate, etc.
Vehicle	CAN bus signals (including steering wheel velocity, brake/gas pedal position, velocity, heading angle, etc.)

Traffic context

Traffic context is the major stimuli for driver intention. Yan et al. (2019) indicated that the "intention emerging process" when drivers form the initial intention to overtake, appears much earlier than the "action executing process" when drivers execute the overtaking manoeuvre and revealed that the lead vehicle speed has a significant influence on initial driver intention to overtake while the complexity of the oncoming traffic (i.e. the number of vehicles, the gap size between them and their speeds) increases the time taken until the overtaking execution. Farah (2013) also investigated the influence of speed difference to the lead vehicle on the decision to overtake but did not include any opposing traffic. Perez et al. (2011) proposed an intelligent automatic overtaking system on two-way roads which can suggest whether to overtake by analysing the preceding environment with real-time variables such as time-to-collision, width and length of the preceding vehicle, differential global positional system and inertial measurement unit. Leonhardt et al. (2018) presented a model for the recognition and prediction of lane changes based on both driver-based input and the traffic situation, particularly the discrete levels of occupancy for each lane. The prediction of overtaking manoeuvres based on the traffic situation is usually addressed by gap acceptance models to assist the decision-making of accepting an available gap as seen in the work of Farrah et al. (2009) and Hassein et al. (2017). Unfortunately, a definition of latent critical gap required in these models are not clear and logistic regressions realized in these models can be overly restrictive in more complex traffic scenarios. Farah et al. (2009) studied the impact of traffic conditions, road geometry and driver characteristics on the decision to overtake but limited their work to two combinations of speeds for the lead and oncoming vehicles employed in driving simulator experiments. Recently, Hassein et al. (2017) performed similar analysis to the study of Farah et al. (2009) but real-world field data was used and their study is limited to a single oncoming vehicle and single target speeds for all involved vehicles. Gray and Regan (2005) also investigated different overtaking situations with oncoming traffic on rural roads in comparative driving simulator studies.

There are many kinds of sensors used to capture the surrounding traffic context such as cameras, radar and lidar systems. Most of the traffic information can be obtained from ADAS with the most popular vision-based ADASs such as LDW and LKA. Vision-based LDW is able to compute the distance between the host vehicle and the lane boundary, the vehicle lateral velocity and acceleration, yaw angle, road curvature, … (Beauchemin et al., 2012). Radar-based ACC can detect the relevant distance between the host vehicle and the front vehicles (Vahidi & Eskandarian, 2003). McCall et al. (2004) proposed a modular scalable architecture to capture surrounding environment, using radar and video devices to obtain the forward, rear and side information. The SWA system helps scan the area of rear and side vehicles up to 50m behind the vehicle, based on at least two radars mounted under the side mirrors (Doshi et al., 2011). These authors also evaluated the impact of different sensors on the prediction of driver intention. The prediction of lane change intention based on sensor data is also seen in the study of Kumar et al. (2013) to obtain the lane information given by a lane tracker, vehicle position and its derivation, …. However, a digital map with GPS, a space-based navigation system, can provide more precise information about vehicle location, road type and road geometry, as indicated in the study of Berndt et al. (2008), even in rough weather conditions when the camera and radar system cannot work. Moreo and Izquierdo (2009) introduced an interactive multiple-model based approach to predict lane change manoeuvres by using the GPS/IMU (inertial measurement unit) sensors to collect the vehicle position data.

Driver behaviours

Driver behavioural signals are also observed to allow earlier prediction of characteristic preparatory measures preceding the execution of a manoeuvre. Driver eye movement can be classified as either intention-guided movement in which eye fixation or saccades were done on purpose, or nonintentional-guided eye movement caused by distractions. Moreover, intention-oriented eye movement also can be viewed as the cognitive progress of either information gathering (i.e., before the manoeuvre is initiated) or action execution (i.e., when the manoeuvre is operated). Caceres et al. (2007) indicated that the driver's intention at an information gathering step is less likely to change when compared with that in the action execution step. Eye movement of the distracted driver cannot reflect the driver's intention and the intention inference results cannot be trusted (Shinar, 2008). However, eye movement is still a useful signal for intention decoding and inference (Borji et al., 2015). Many prior research has applied the eye-tracking technique to predict lane change intention (Zhou et al., 2008, 2009 & 2010; Doshi & Trivedi, 2008 & 2009) and it has been proved that eye movement information does increase the accuracy rate of prediction and reduce the false alarm rate. To overcome the challenges of effects caused by lightness, glass and hair near the eye on eye-tracking performance, some robust algorithms for eye movement detection have been proposed (Timm & Barth, 2011; Wang et al., 2015; Martin et al., 2018). The eye-tracking system available on the market can be categorized into intrusive wearable glass type and non-intrusive camera-based system mounted on the vehicle dashboard. In driving silmulator experiments, the eye data can be captured by the SMI (SensoMotoric Instruments) eye-tracking system, as in the study of Lethaus et al. (2013a) who evaluated how early the eye gaze information can reflect the driver intent and how many gaze features used for intention recognition. They concluded that a 5s window for the eye data is better for intention prediction because the 10s window carries more noise.

Similar to eye movement, head motion is another cognitive process for information gathering. It has been even proved that head movement is a more important factor than eye movement for driver intention prediction (Jain et al., 2016) and has also been widely used in many past DII research (Dogan et al., 2008; Girshick, 2015; Lv et al., 2015). Chutorian and Trivedi (2009) concluded that there has been a variety of head pose estimation algorithms used to track head movement. According to the current head-tracking algorithms, those developed with multicameras shows better performance than a monocular camera algorithm despite of its high system costs. However, the in-vehicle head-tracking system has one significant challenge of the online computing ability of the onboard processor to deal with large amount of data. The sensitivity and specificity of the eye-tracking system can be improved by 10% using the data processing method in the study of Ahlstrom et al. (2012). Another challenge is the noise issue of captured images, caused by vibration from the road and lightness variation issues in the vehicle cabinet.

In addition to camera-based driver eye- and head- tracking system, some other driver behaviours such as the foot, hand and body gestures were also recorded through a camera in some research (Tran et al., 2012; Das et al., 2015; Tran & Trivedi, 2012). Eshed et al. (2015) studied real-time and early prediction of overtaking intent and manoeuvres based on a naturalistic dataset of driver, vehicle and surroundings. Their data were taken from distributed vision sensors to track head pose, hand and foot motions, surround vehicle trajectories, lane and road geometry, surround visual. The results indicated that driver cues (i.e., foot) and surround cues (i.e., visual cues, lidar/radar) are better for early prediction rather than lane deviation and the steering information. Doshi et al. (2011) also uses head pose, among other cues to predict the possibility of crossing the lane marking in a 2s window before the actual event. Other studies which applied driver-based input approaches include Ohn-Bar et al. (2014), Doshi and Trivedi (2011), Oliver and Pentland (2000) and Jain et al. (2015). However, driver-based input may be short-lived and misleading as the result of the ever-increasing introduction of automation

Electroencephalography (EEG) is a brain action measuring device that measures the flow of brain electric current with non-invasive electrodes on the scalp. EEG is also an important sensor for detecting a human mental state. EEG has been widely used to monitor driver workload and driver status such as drowsiness, happiness, sadness, mental fatigue and abnormal conditions (Tiwari & Giripunje, 2014). EEG has also been used in driver steering intention prediction with the prediction accuracy of 65%-80% (Ikenishi et al., 2008). However, in the real-world driving environment, EEG signals contains lots of noise and can be affected by head movement, making it impractical to be used (Alonso and Gil, 2012)

Vehicle dynamics

The vehicle state subsuming information about vehicle dynamics (i.e. velocity, acceleration, yaw rates, …) and the position and orientation of the vehicle in the road is most commonly used to compare the observable vehicle state sequence with expected sequences, as seen in the work of Kumar et al. (2013) to predict lane change intention, the work of Bi et al. (2015) to detect driver normal and emergency lane-changing intentions or the work of Liebner et al. (2012) to study driver intent inference at urban intersection. Also, Ali et al. (2013) predicted overtaking behaviour using the kinematic features such as velocity, longitudinal acceleration and movement angle of two vehicles involved, especially in all instantaneous values without any assumed constants.

Vehicle data collected from the vehicle CAN bus can be processed with large amount of data at high transfer speed. Blaschke et al. (2008) predicted overtaking manoeuvres via CAN bus data with collected indicators such as brake pressure, accelerator pedal value, accelerator pedal speed, … In terms of lane change intent, throttle pedal position, brake pressure, cross-acceleration, steering wheel angle, steering wheel angle velocity, yaw rate and velocity are collected from CAN bus in the study of Morris et al. (2011) and Berndt et al. (2008). Schmidt et al. (2014) proposed an explicit mathematic model of the steering wheel to recognize lane change intent. Lethaus et al. (2011) constructed a driver intention recognition model based on artificial neural networks (ANNs), which was fed with both CAN bus data and driver gaze information. In the driving simulator environment, the input signals into a driver lane change/keep intention inference model can be the steering wheel angle, steering angle velocity, lateral acceleration, relative speed of the front vehicle, transmission position, acceleration pedal position (Li et al., 2014; Hou et al., 2011).. However, vehicle dynamics data gives delayed information compared to the signals from driver behaviours and traffic situation to infer the driver intention, once the manoeuvre has been already initiated, because it can be considered as direct responses to the driving actions. Still, the vehicle data is an important data source to increase the accuracy of the intention identification because not all driver intention is realized into observable actions.

Chapter 3: Research methodology

3.1. Selected variables

Due to limited time and resources, input signals and sensors used for prediction are sourced from the vehicle dynamics and traffic context only, ignoring the factor of driver behaviours. Our study focuses on four available kinematic vehicle variables of real-time instantaneous values used as model inputs as follows:

- **Longitudinal speed** (kilometres/hour) of the driven vehicle
- **Longitudinal acceleration** (meters/second^2) of the driven vehicle
- **Steering wheel angular rate** (degrees/second) or **heading angular rate** (radians/second) of the driven vehicle
- **Headway** (seconds) between the driven vehicle and the preceding vehicle

To classify whether an overtaking manoeuvre is safe or dangerous, the value of headway at the turning-point of steering wheel angular rate to start overtaking is judged. On Dutch roads, (too) short headway times was registered by police as the cause of 80% off all rear-end collisions and serious rear-end crashes made up 36% of all registered serious crashes and 25% of all registered fatal crashes from 2007-2011 that the Dutch government has paid much attention to keeping safe headway in many traffic safety campaigns (SWOV, 2012). In overtaking manoeuvres, there is also a risk of rear-end accidents that the overtaking vehicle no longer maintains the safe distance from the car ahead in preparation for overtaking (Rajalin et al., 1997). According to SWOV (2012), passenger car drivers are advised to keep two-second headway in the Netherlands to allow sufficient reaction time to commence emergency braking, if necessary, under various circumstances. This 2s rule is also known in Belgium, Finland, New Zealand and Austria. However, this critical headway value is not the same for every driver and varies from less than one second to about two seconds because the reaction time is a function of the driver's alertness, expectation and situational complexity (Lamm et al., 1999).

In practice, Hasen and Minderhoud (2003) collected data on the headway between passenger cars on a Dutch motorway, using an instrumented vehicle. They realized that as the speed of vehicle increases, the average headway time decreases and at the speeds from about 90 km/h, the average headway of passenger cars is less than one second. Hegeman (2008) also indicated that more than half of observed overtaking headways between passenger cars in the Netherlands are smaller than 1s. In developing an automated driving system for the overtaking manoeuvre, Kakade (2018) used the control strategy called 'Constant time gap' with a headway threshold of 0.8s. However, **the chosen headway threshold in our study is 1.2s** that any overtaking manoeuvres which records a headway smaller than 1.2s at the turning-point of steering wheel angular rate are classified as "Dangerous".

3.1.1. Data collected from driving simulators

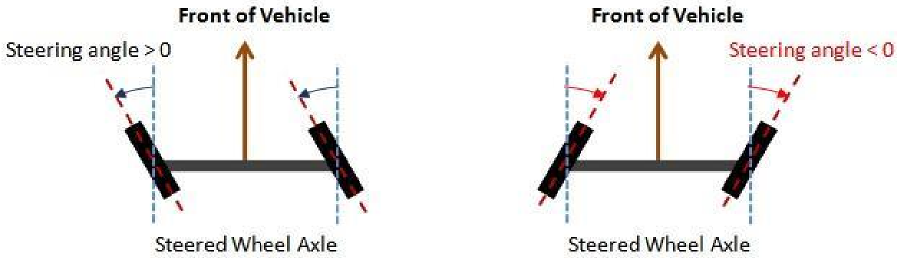
Driving simulators provide an artificial environment best used for drivers to experience critical driving situations without severe ethical and safety concerns. Although driving simulators may not always provide ecologically valid results (Farah et al., 2019), their main advantages are the large number of accurately measured variables extracted such as headway, time to collision, lateral lane position of the driven vehicle, … without the problem of missing signals as often occurred in naturalistic driving. Also, tests using driving simulators are used for years to design and evaluate many active safety systems (e.g., system acceptance (Lubbe & Davidsson, 2015), EuroNCAP scenario definitions, …).

Figure 3. 1. Experiment in driving simulation

The driving simulator experiment in our study was conducted at Transportation Research Institute (IMOB) of Hasselt University. The fixed-base driving simulator was equipped with a steering wheel, an accelerator pedal and a brake pedal. The driving scene was shown on one screen as presented in Figure 3.1. The driving scenarios were designed to allow the driver overtake on a two-lane rural road with the presence of oncoming traffic on the opposing lane.

One young male university student of the age 25 who had owned a driving license for around 3-4 years was invited as the only participant in the experiment. During the experiment, the participant first underwent several test trials to get familiar with the driving simulator environment, the scenery and the overtaking task, which was followed by repeated experimental trials. In the end, the total of 40 legitimate overtaking manoeuvres were recorded. Although the raw dataset was recorded in milliseconds, our study dataset prepared for model training and testing was processed and recorded in seconds. Our considered variables, including longitudinal speed, longitudinal acceleration, steering wheel angle and headway were directly extracted from raw dataset. The steering wheel angular rate was then derived from the steering wheel angle values which is the difference between the current and previous angle values, positive to the left as shown in Figure 3.2.

Figure 3. 2. Definition of steering angle



3.1.2. Data collected from naturalistic driving

The advantage of naturalistic driving study is to offer much wider perspectives in understanding normal traffic behaviour inn normal everyday traffic situation. UDRIVE is the first large-scale European naturalistic driving study on cars, trucks and powered two-wheelers, using recorded details of the driver, the vehicle and the surroundings through unobstrusive data gathering equipment and without experimental control (Yvonne et al. 2016). Similar studies include PROLOGUE, INTERACTION, 2BeSafe, DaCoTA, SemiFOT and Large Field Operational Tests (e.g., euroFOT, TeleFOT).

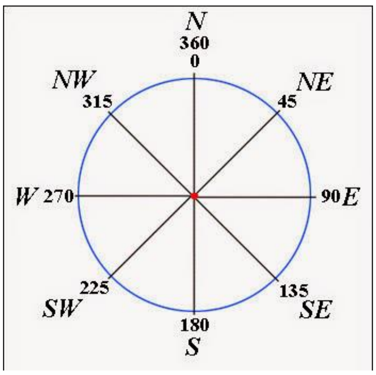
In our study, data was also collected from naturalistic driving on two-lane roads in the built-up areas in Hasselt as shown in Figure 3.3.a. The vehicle testbed is a commercial vehicle equipped with multiple radar and lidar sensors as shown in Figure 3.3.b. Data was extracted mainly from GPS positioning and CAN bus vehicle dynamics. One IMOB's young male staff with experienced driving of more than 10 years was invited to drive and overtake as usual without being told of the experiment objectives. Another assistant was sitting next to the driver to record the exact time point of executing the overtaking manoeuvre. The driver drove the vehicle for about an hour and a total of 28 overtaking manoeuvres were recorded. Three considered variables, including longitudinal speed, heading angle and headway were directly extracted from the raw dataset in the timeframe in seconds. Some missing values of headway can be replaced by the previous value. The longitudinal acceleration in meters/second^2 equals the difference between the current and previous speed values, divided by 3.6. The heading angular rate (rather than its absolute angle values) can be used as a similar measure to the steering wheel angular rate. Because the heading angle values taken from GPS are based on a compass rose as indicated in the Figure 3.4, the heading angular rate equals to the difference between the previous and current heading angle values to be comparable to the steering wheel angular rate (i.e., negative as rotating clockwise).

Figure 3. 3. Experiment in naturalistic driving

a. Driving on an urban road in Hasselt

b. The vehicle testbed

Figure 3. 4. The compass rose

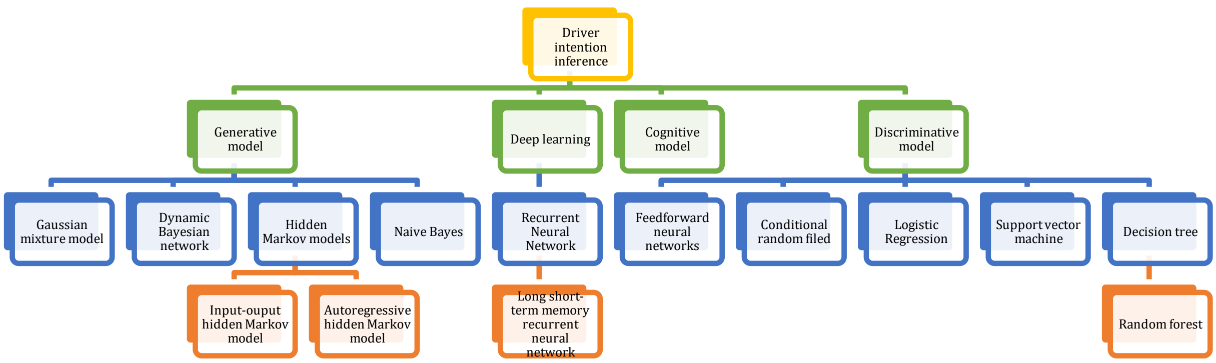


3.2. Driver intention inference algorithms

Conventional intention inference algorithms can be roughly divided into the following groups: mathematic model, driver cognitive model and the widely used machine learning (ML) models. Because it is difficult or even impossible to build an accurate mathematic model for human mental state, the ML techniques with a rich theory background provide an efficient way to learn knowledge from naturalistic data and even achieve an end-to-end learning process with some advanced deep learning methods. Also, the learning of long-term dependency between driver behaviours and traffic context enables ML algorithms to significantly increase the inference accuracy. Importantly, the ML technique rather than mathematic models can deal with high dimensional real-time traffic context and driver behaviour data of large volume. Therefore, the ML algorithms are widely adopted because of their ability to construct the inference system by fusing a large number of signals (i.e., up to 200 sensor signals adopted in the intelligent vehicle in the study of Morris et al. (2011)). However, the major limitation of using ML algorithms is data collection that insufficient data volume will lead to overfitting and bad inference results and data manual labelling is time-consuming. Higher computational burden both for the financial and temporal costs in training and testing ML algorithms is another limitation.

Machine learning algorithms can be divided into generative models and discriminative models. The generalized model relies on probability theory and prior knowledge about the work, whereas the discriminative model does not require statistical information. The generative models provide a joint probability distribution over the observed and target values, which can generate both the inputs and outputs according to some learned hidden states. The discriminative model only provides the dependence of the target on the observed data and usually can be generated from the specific generative models through the Bayes rule. Compared with the discriminative model, the generative model is less easy to be trained because multiple models are trained simultaneously and each model is provided to each class based on the different probability distribution. As mentioned in Doshi and Trivedi (2011), discriminative models provide a better result on a single target problem than the generative models, whereas the generative models are more suitable for multitarget problems. Recently, deep learning methods are also employed in the studies of driver intention inference systems, as shown in Figure 3.5.

Figure 3. 5. Taxonomy of algorithms for driver intention inference system



Source: Adapted from Adopted from Yang et al. (2020)

3.2.1. Cognitive Models

Salvucci (2004&2006) introduced a real-time system for detecting driver lane change intention based on a mind-tracking architecture and implemented in the study of Adaptive Control of Though-Rational. The system suggests four steps, including collecting data, simulating model, tracking action and inferring thought. During the simulation, several models were run simultaneously within the system which detected the driver's intentions by examining the "thoughts" of the best matching model. Although the mind-tracking system achieved 85% accuracy with a 4% false alarm rate for lane change intention detection, investigations were conducted exclusively in simulators . Luzheng et al. (2015) constructed a queuing network cognitive architecture to detect the normal lane change and emergency lane change manoeuvres. The intention was detected based on a threshold of root-mean-square error (RMSE) value with a high accuracy rate of 90% and a low false alarm rate of 0.294%. This method can be easily applied to real-world context rather than intelligent inference methods based on eye gaze and head movement. However, the steering wheel angle signal as the only input into the algorithm cannot help infer the driver manoeuvre at a very early stage or before the manoeuvre happens. Ohasi et al. (2004) also proposed a driver recognition method based on the HMM in the framework of a cognitive model of human behaviour to classify between emergency lane change, normal lane change and lane keeping.

3.2.2. Generative Models

Generative models such as Hidden Markov Models (HMMs) and Dynamic Bayesian Networks (DBNs) are widely used in previous intention inference (Schmidt et al., 2014; Li et al., 2014; Jang et al., 2014; Doshi and Trivedi, 2009; Campbel & Bajcsy, 2015). Pentland and Liu (1997) used the HMM to recognize seven kinds of driver intention. Berndt et al. (2008) used the HMM to investigate early lane-change intention. Oliver and Pentland (2000) also used the HMM to predict overtaking manoeuvres with a high level of reliability approximately one second before their performance. Just like many other studies, the authors failed to assess false-positive predictions of overtaking manoeuvres and the algorithm was not validated for other situations or drivers for generalizability of the findings. Pech et al. (2014) proposed a driver head-tracking system based on Naive Bayesian system to classify the glance area of the driver. In the study of Kasper et al. (2012), a lane change detection model was based on the object-oriented Bayesian network which was constructed by various sub-Bayesian networks with different functions. This system was designed according to the modularity and reusability of the Bayesian network to facilitate system extension according to different requirements. Li et al. (2016) proposed an integrated intention inference algorithm in which a preliminary output from the HMM was further filtered using the Bayesian filter (BF) method to make the final decision. The HMM-BF framework achieved a recognition accuracy of 93.5% and 90.3% for the right and left lane changes, respectively. A driver lane change behaviour classifier can also be based on a hybrid model that combines a Bayesian network and Support Vector Machine (SVM) (Morris & Doshi, 2011). Hou et al. (2011) constructed a lane change intention recognition method based on the continuous HMM and concluded that the continuous HMM with six hidden states and 1.5s window size (i.e., data collected between 0 and 1.5s prior to the vehicle crossing the lane) gave the best classification result (95.48%). Another context-based highway lane change intention system based on HMM in the study of Polling et al. (2005) suggested that additional inputs of context data lead to a high false-positive result rate and the classification performance was worse than the system with vehicle state information only. It indicates that the HMM has limited ability to capture the context information during the lane change process. More powerful algorithms such as double-layered HMM and input-output HMM are suggested (Jain et al., 2016).

3.2.3. Discriminative Models

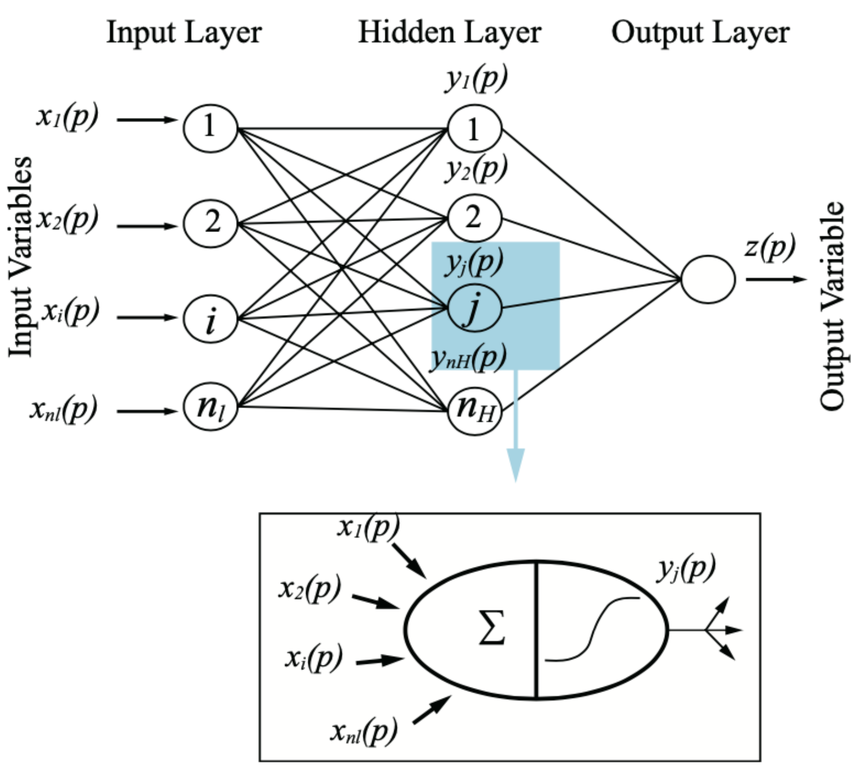
Discriminative models such as support vector machine (SVM) and artificial neural network (ANN) are also widely used in intention inference because of the rich background theories and the successful application experience. Lethaus et al. (2013b) used different algorithms and concluded that the performance of ANN was the best, as compared with other two methods, including Bayesian networks and Naive Bayesian. Mandalia and Salvucci (2005) proposed a driver lane change and lane keeping intention classification method based on SVM. Morris et al. (2011) and Doshi et al. (2011) used a Bayesian extension to the SVM algorithm, namely, the relevance vector machine to classify the driver lane change (right and left) and lane keeping intentions. The false alarm rate of the system decreased with the use of multiple detection suppression techniques, helping the classifier achieve 80% accuracy. However, the online classification results were worse in a real-time environment than in the experimental environment. In the study of Campbell (2015), SVM, random forest and logistic regression were algorithms used to identify three kinds of driver intentions: lane keeping, preparing for lane changing, and lane changing. The SVM was then reported to achieve the best classification performance. Lethaus et al. (2011) proposed a lane change intention recognition method based on ANNs and indicated that head rotation had consistent gains between 1.5 and 2.5 s prior to the lane change manoeuvre. Kumar et al. (2013) combined the SVM and Bayesian filter (BF) to construct an algorithm which can realize prediction of the intention in an average of 1.3s in advance and achieve a maximum prediction horizon of 3.29s. To reduce the false alarm rate, the performance of the lane tracker system was suggested to be improved. Dogan et al. (2008) introduced and compared three machine learning methods, which were the feedforward neural network (FFNN), recurrent neural network (RNN), and SVM, based on four evaluation criteria, including the mean value of prediction horizon, the number of the correctly recognized lane change, the number of not recognizing the lane change, and the number of false alarms. The results showed that SVM gave the best results followed by RNN and the classifiers were able to predict the lane change 1-1.5 s prior to the vehicle crossing the lane.

In particular case of overtaking prediction, both Khodayari et al., (2010) and Ghaffari et al. (2013) used the concept of Artificial Neural Network (ANN) with the FFNN as its most common network type. An ANN is generally an information processing system replicating the design and functioning of human brain, comprised of highly connected processing elements/nodes called neurons connected by weighted links. In FFNN, input is fed into the network in the input layer, processed in the hidden layers and transformed into an output in the output layer, mapping only raw data to categories (Figure 3.6). The feedforward phase means that input signals propagate in forward direction (layer by layer) to produce output and the backward propagation process of an error between computed and observed values of the target variable modifies the connection strengths (weights). ANN model can be described in the following formula as:

$$O_k = g_2\left[\sum_{j=1}^{M} W_{kj}\, g_1\left(\sum_{i=1}^{N} W_{ji}x_i + W_{jo}\right) + W_{ko}\right]$$

, where x_i is the input value to node i, $O_k$is the output at node k, $g_1$and g_2 are respectively nonlinear and linear activation function of the hidden and output layers. N and M respectively represent the number of nodes in the input and hidden layers. W_{jo} and W_{ko} are biases of the j[th] node in the hidden layer and the k[th] node in the output layer. $W_{ji}$is the weight between the input node i and the hidden node j and W_{kj} is the weight between the hidden node j and the output node k.

Figure 3. 6. FFNN architecture with one hidden layer

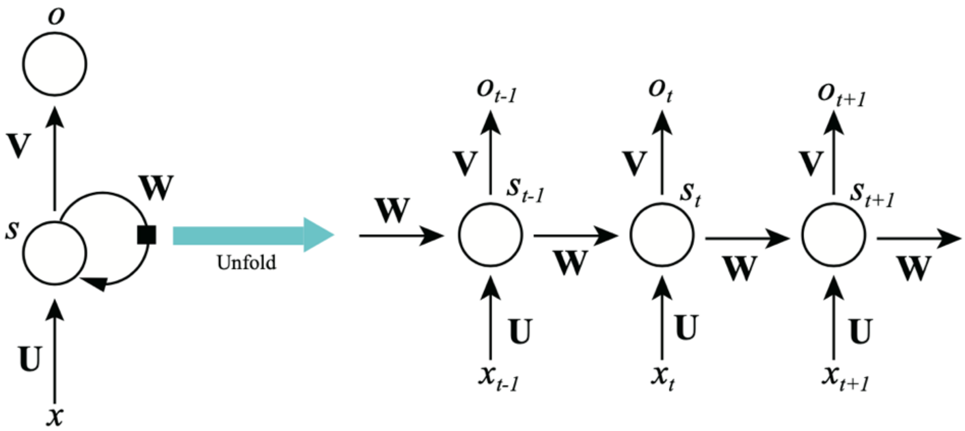


Source: Caihong et al. (2018)

3.2.4. Deep learning Methods

Recently, tremendous achievement has been made in the deep learning area related to many computer vision tasks such as image classification, segmentation and object detection domains (Lv et al., 2015; Girshick, 2015) . This achievement has been facilitated by the development of deep learning theories, computation hardware platforms, software systems and large-scale annotated dataset. The deep convolutional neural network has been widely adopted in many intelligent and automated vehicles (Krizhevsky et al., 2012). Meanwhile, the recurrent neural network (RNN) also achieved significant results on natural language processing and image captioning areas (Jain et al., 2015&2016).

Figure 3. 7. A simplified recurrent neural network architecture



Source: Yang et al. (2020)

RNNs are a strict superset of feedforward neural networks (FFNN), augmented by the inclusion of recurrent edges that span adjacent time steps and thus are powerful models for sequential data, certainly fitted in the case of driver intention inference which is not an instance detection task and should take previous driver behavioural data into consideration. In other words, the RNN model is applied to learn the temporal dependency between the input data, exhibiting the dynamic temporal behaviour of a sequence by forming a directed connection between previous states and the current state (Zyner et al., 2018; Morton et al., 2017; Olabiyi et al., 2017). Figure 3.7 illustrates a basic structure of the RNN model that the right-side illustration is the unfolded version of the left circuit diagram. $x, s \ and \ o$ represent the input, hidden states and the output of the RNN, respectively. $W, U \ and \ V$ are parameters for weights. At time t, nodes receiving input along recurrent edges receive input activation from the current example x_t and also from the hidden nodes s_{t-1} in the network's previous state to calculate output o_t, given the hidden state s_t at the time step. Thus, input x_{t-1} at time $t-1$ can actually influence the output o^t at time t by way of these recurrent connections.

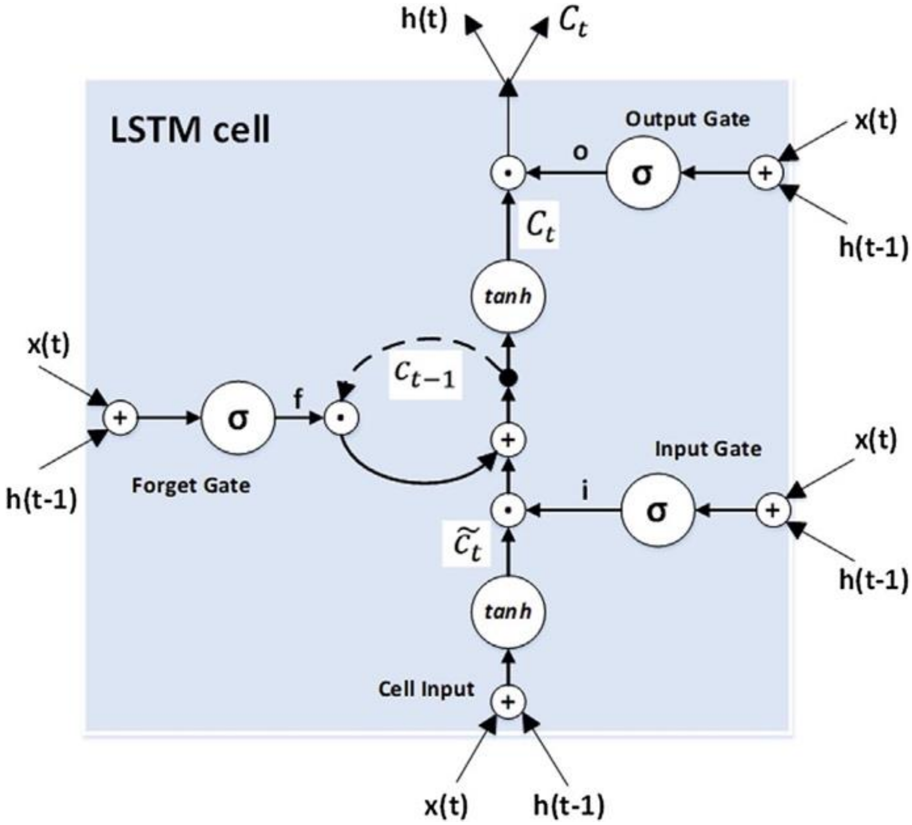
The RNN model can be described as two equations necessary for computation at each timestep on the forward pass as follows,

$$s_t = f(W_x x_t + W_s s_{t-1} + b_s)$$

$$o_t = softmax(W_o s_t + b_o)$$

where $W_x, W_s \ and \ W_o$ are the model parameter matrix for the input, hidden states and output; $b_s \ and \ b_o$are the bias vectors which allow each node to learn an offset. Although the RNN shares the same $W_x, W_s \ and \ W_o$ at each time step to reduce the number of training parameters, RNN still suffers another serious problem known as the gradient vanishing or exploding (Bengio et al., 1994) to remember long-term dependency. Therefore, the long short-term memory (LSTM) scheme was also proposed to increase the memory ability of the RNN model (Hochreiter & Schmidhuber, 1997) by introducing three extra gates, known as the input gate, forget gate and output gate which cooperate with each other to control how much information should be remained and forgot. Figure 3.8 shows the LSTM cell architecture. The only difference from Figure 3.7 is that LSTM-RNN replaces the hidden unit (normally *sigmoid* or *tanh* activation function) with an LSTM cell.

Figure 3. 8. Illustration of long short-term memory cell structure



Source: Yang et al. (2020)

First, the forget gate controls what information to throw away. Then, the input gate chooses new information to be updated and stored and the output gate controls the candidate layer output. The function of these gates in the LSTM cell is represented as these following mathematic functions:

$$f_t = \sigma(U_f x_t + W_f s_{t-1} + b_f)$$

$$i_t = \sigma(U_i x_t + W_i s_{t-1} + b_i)$$

$$o_t = \sigma(U_o x_t + W_o s_{t-1} + b_o)$$

, where σ represents the *sigmoid* function, x_t as the current input vector, s_{t-1} as the previous layer output. f, i, and o are the forget gate, input gate, and output gate. U, W, and b are the corresponding model parameters. The candidate cell state can be represented as:

$$\tilde{c}_t = tanh(U_c x_t + W_c s_{t-1} + b_c)$$

The C_t in the center of the Figure is the internal memory cell state of the LSTM unit which is the combination of previous c_{t-1} and current candidate states as follow

$$C_t = f_t * c_{t-1} + i_t * \tilde{c}_t$$

, where $*$ is the element-wise production. Finally, the layer output is the products of the cell state C_t and the candidate output from the output gate.

$$s_t = o_t * tanh(C_t)$$

The RNN outperformed the quadratic discriminate analysis model in the study of Zyner et al. (2018) to infer the driver's intention when entering an intersection. Similarly, Jain et al (2016) compared the lane-change intention inference performance of the LSTM-based RNN with multiple HMMs, considering input data such as driver head rotation and traffic context from the GPS and digital map. This deep learning algorithm showed a more significant advantage in prediction accuracy and larger prediction horizon because of higher ability to capture long-term dependence of previous driver behaviours and traffic context, despite of their higher computational burden. In comparison with the feedforward neural network (FFNN) which trains the nontemporal discriminative model with the statistic features of the sequence (Jain et al., 2015), Yang et al. (2020) proved that the detection rate of lane-change using the LSTM-RNN was higher.

Figure 3. 9. Visualization of the amount of input information used for prediction

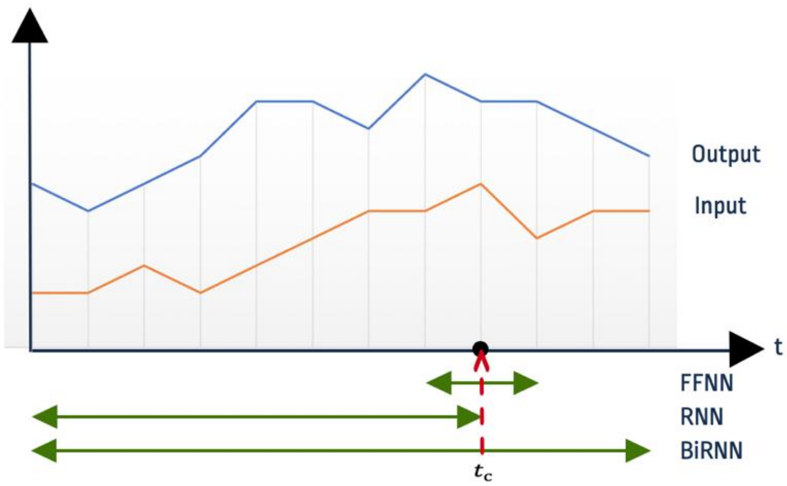
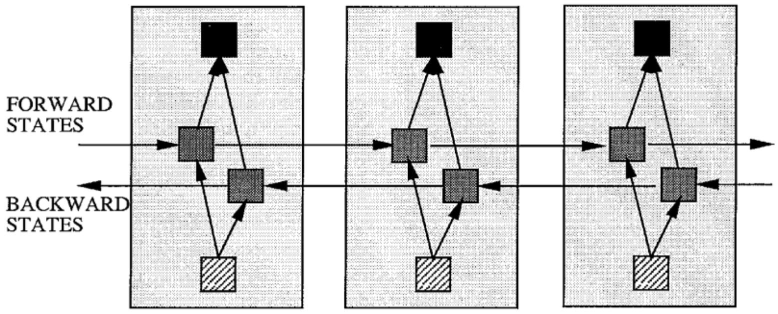


Figure 3.9 illustrates the amount of input information used for prediction with different kinds of neural networks. Instead of using a fixed number of input vectors at the current time frame (t_c) as done in the FFNN structures, the RNN architecture can make use of all the available input information up to the current time frame to predict output. Because future input information coming up later than t_c is usually also useful for prediction, a bidirectional recurrent neural network (BiRNN) is proposed that can be trained using all available input information in the past and future of a specific time frame (Schuster and Paliwal, 1997). Figure 3.10 illustrates the general structure of the BiRNN shown unfolded in time for three timesteps. The idea is to split the hidden neurons of a regular RNN in two parts: one responsible for the positive time direction (forward neurons) and one for the negative time direction (backward neurons). Outputs from forward neurons are not connected to inputs of backward neurons, and vice versa. Therefore, the BiRNN can be trained in the same algorithms as a regular unidirectional RNN because these two types of hidden neurons do not interact to each other.

With both time directions taken care of in the same network, the objective function can be minimized by simultaneously training input information both in the past and the future of the currently evaluated time frame. Similarly, a bidirectional LSTM-RNN (Bi-LSTM-RNN) is obtained by replacing the hidden unit (normally *sigmoid* or *tanh* activation function) in the BiRNN with an LSTM cell. Schuster and Paliwal (1997) proved that the BiRNN in classification experiments on both artificial and real data shows better prediction results than the regular RNN. Yang et al. (2020) also indicated a better performance of Bi-LSTM-RNN than the LSTM-RNN in predicting right/left lane change and lane keeping.

Figure 3. 10. The Bi-LSTM-RNN structure shown unfolded in time for three timesteps



3.2.5. Selected methodology

Our goal is to build a model which anticipates dangerous overtaking manoeuvres before they occur which means predicting the point of the headway reaching its threshold before the turning-point of steering wheel/heading angular rate. The main tasks require modelling of driving context and vehicle dynamics taken from different sensors and then recognizing variable time occurrence of informative cues necessary for anticipation. In other words, our end-to-end trainable model via back propagation must (i) model the temporal aspects of the problem; (ii) fuse multiple sensory streams; and (iii) anticipate manoeuvres.

Two building blocks of our architecture are RNNs (Pascanu, 2012) and LSTMs (Hochreiter and Schmidhuber, 1997). A Recurrent Neural Network (RNN) based architecture equipped with Long Short-Term Memory (LSTM) units is proposed to learn rich representation for prediction and capture temporal dependencies. Both regular and bidirectional LSTM-RNN systems are investigated and compared to the baseline algorithm of a Feedforward Neural Network (FFNN). In addition, appropriately fusing the information from different sensors is crucial for the final prediction performance. While simple sensory approaches like concatenation of feature vectors is used in FFNN-based method (as specified in section 3.3.1), RNN-based method learns a neural network layer for fusing the temporal streams of data coming from different sensors.

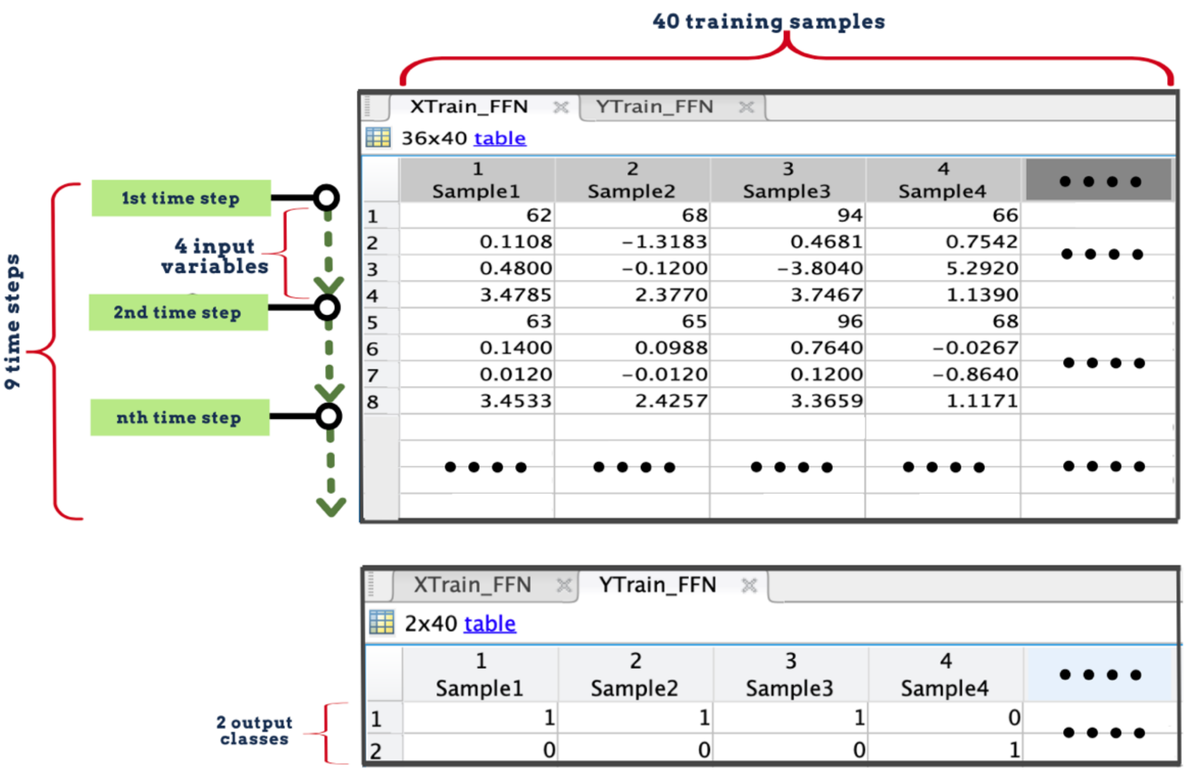
Our work is directly inspired by previous works, including the work of Jain et al. (2015 & 2016) who anticipate different types of vehicle manoeuvres and compare results derived from different learning algorithms such as the LSTM-RNN, Autoregressive Input-Output HMM, Random-Forest, SVM, …; the work of Yang et al. (2020) who further include an ensemble learning-based method combining three bidirectional LSTM-RNNs into performance evaluation of lane-change prediction and the work of Zyner et al. (2018) who proposed a RNN solution for predicting driver intention at unsignalized intersections.

3.3. Workflow in MATLAB

3.3.1. Data pre-processing

Building the network input XTrain and output YTrain for training purposes in different application scenarios is a critical step. In terms of application scenarios in Feedforward Neural Network (FFNN) which trains the nontemporal discriminative model by concatenating the feature vector at each step into a large feature set, the 9-D temporal sequence data in our study are transformed into a 36 x 1 feature vector for each training sample in the network input XTrain, as illustrated in Figure 3.11. This 36-dimensional feature vector is much smaller compared with the 3840-dimensional vector in the work of Jain et al. (2015) mainly because of their large number of input variables. The network output YTrain comprises of 40 classification vectors of 2 x 1 dimension, corresponding to 40 training samples collected from simulation and 2 classes for each sample (i.e., “Safe” and “Dangerous”). The naturalistic data collected for further testing purposes also needs to be pre-processed in the same way as the data set collected from simulation.

Figure 3. 11. Data pre-processing in the application of FFNN

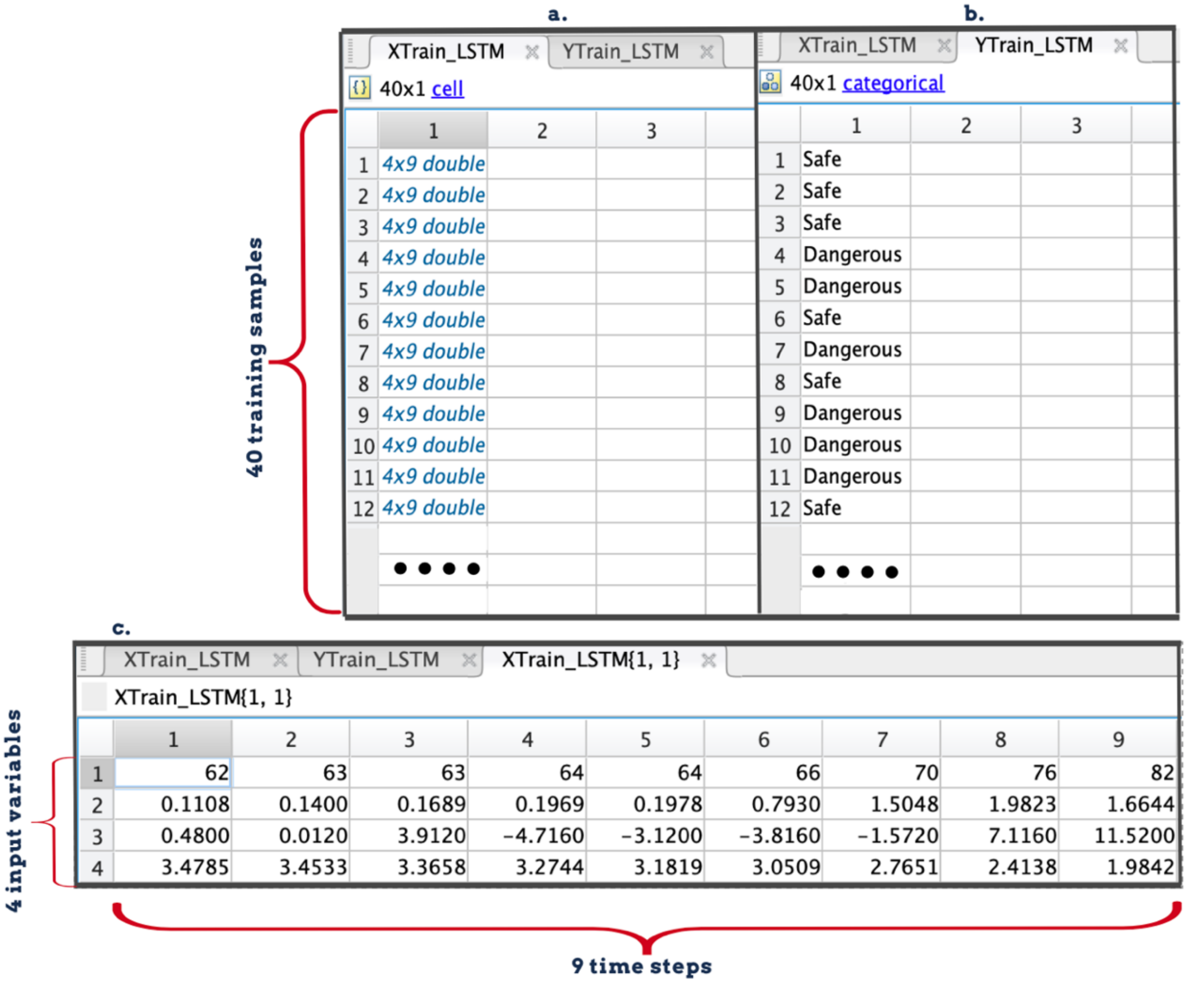


	1 Sample1	2 Sample2	3 Sample3	4 Sample4	••••
1	62	68	94	66	
2	0.1108	−1.3183	0.4681	0.7542	••••
3	0.4800	−0.1200	−3.8040	5.2920	
4	3.4785	2.3770	3.7467	1.1390	
5	63	65	96	68	
6	0.1400	0.0988	0.7640	−0.0267	••••
7	0.0120	−0.0120	0.1200	−0.8640	
8	3.4533	2.4257	3.3659	1.1171	
	••••	••••	••••	••••	••••

	1 Sample1	2 Sample2	3 Sample3	4 Sample4	••••
1	1	1	1	0	••••
2	0	0	0	1	

In terms of application scenarios in Long Short-Term Memory – Recurrent Neural Network (LSTM-RNN), the network input XTrain is a 40-by-1 cell array and each cell is a 4-by-9 matrix. XTrain can be described as follows: XTrain contains 40 data sequences collected from simulation, the length of each sequence is 9 and the feature dimension of the sequence is 4. In each sample (i.e., each cell), column data represents a feature vector at a certain point in time with a length of 9. Columns of data are arranged in the row direction to form a time stamp. The Figure 3.12 shows the cell array in XTrain (a) and the first sequence of XTrain after expanding it (c). In the sequence-to-label classification application scenario, the network output YTrain needs to be category type data which means a 40-by-1 category cell as illustrated in Figure b. The naturalistic data collected for further testing purposes also needs to be pre-processed in the same way as the data set collected from simulation. All the data sets are manually pre-processed and transferred from .xlsx files to .mat files in the workspace of MATLAB software.

Figure 3. 12. Data pre-processing in the application of LSTM-RNN



3.3.2. Deep network designer

Feedforward Neural Network

A two-layer feed-forward network is selected and designed with sigmoid hidden neurons and softmax output neurons to classify input vectors, as shown in the Figure 3.13. Although feedforward networks with more layers can learn complex relationship more quickly, our study found the performance of a two-layer feed-forward network satisfactory already. Because increasing the number of neurons in the hidden layer increases the power of network but requires more computation and is more likely to produce overfitting, the number of neurons in the hidden layer is ultimately chosen as 20 after trials and errors.

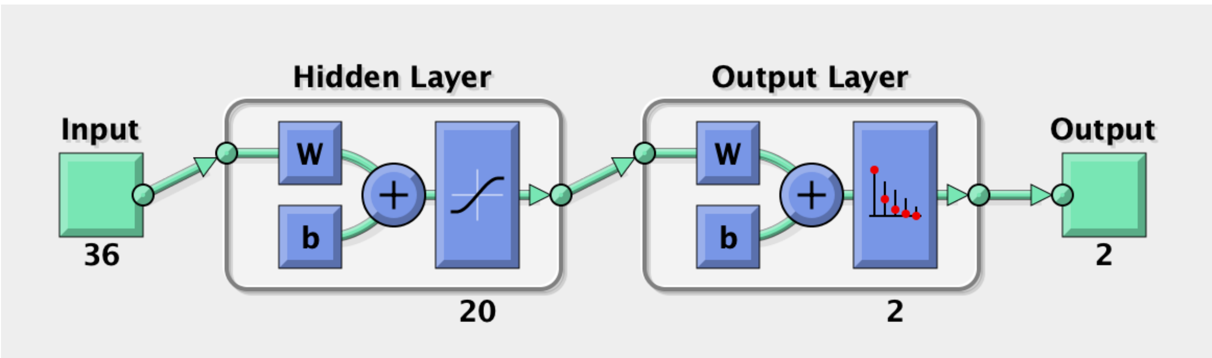
Each neuron receives the input vector of 36 elements. Each input is weighted with an appropriate w. The sum of the weighted inputs and the bias b forms the input to the tan-sigmoid nonlinear transfer/activation function f to compute its own output. A softmax layer employed in the output layer corresponds to a fully-connected layer with softmax as activation function f and two neurons equal to the number of classes desired in the output. The softmax function is known as the normalized exponential and can be considered the multi-class generalization of the logistic sigmoid function (Bishop, 2006). This output layer takes the output of its previous hidden layer as input and applies another set of weights and biases and non-linearity to give a probability distribution over the class variables in the dataset. Generally, the network architecture is considered as a fully-connected network because the neurons in current layer are connected to every neuron in the previous layer by these sets of weights.

A general form of applying a non-linearity to an input time series X can be indicated in the following equation:

$$A_{l_i} = \mathrm{f}\left(w_{l_i} \times X + \mathrm{b}\right)$$

, where w_{l_i}being the set of weights with length and number of dimensions identical to X's, b the bias term and $A_{l_i}$the activation of the neurons in the layer l_i. In other words, each time stamp has its own weight and the temporal information is therefore lost as time series elements are treated independently from each other. Thus, the network architecture itself indicates that FFNN does not exhibit any spatial invariance.

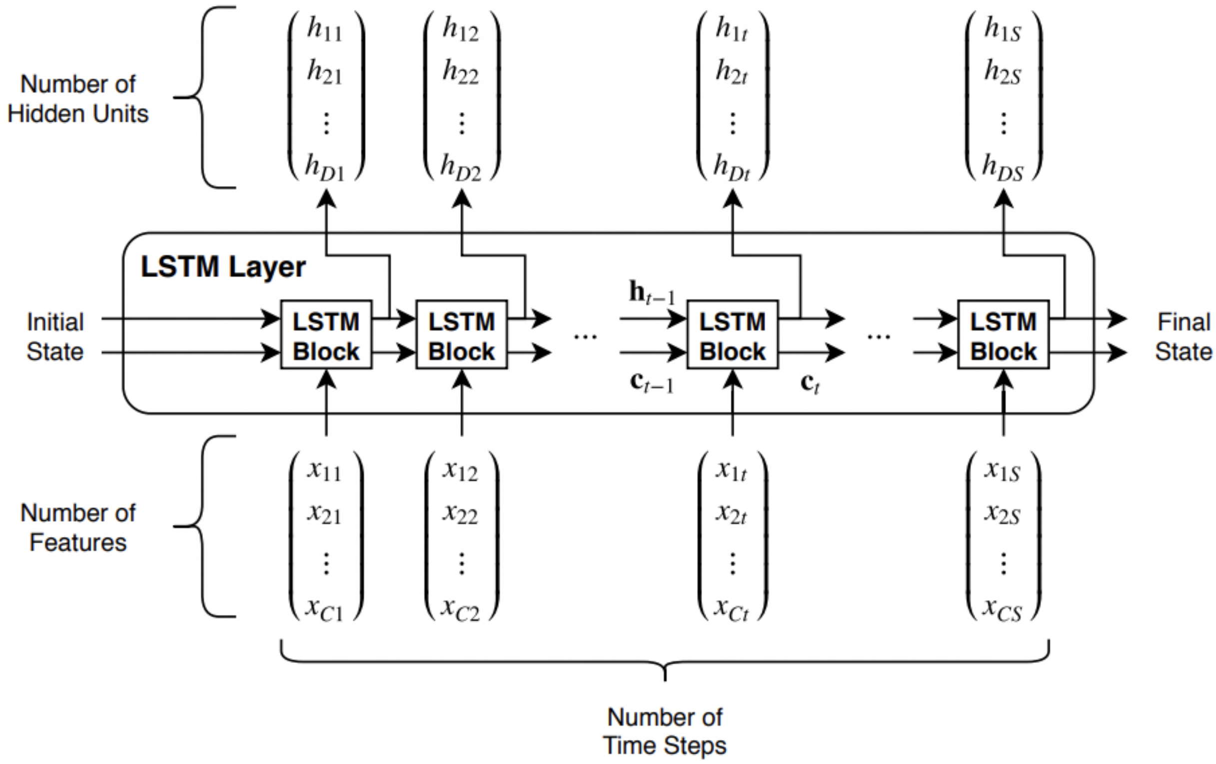
Figure 3. 13. The design of FFNN



(Bidirectional) Long Short-Term Memory – Recurrent Neural Network

The diagram in Figure 3.14 illustrates the flow of a time series X with C features (channels) of length S through an LSTM layer. In the diagram, at time step t, the LSTM block uses the current state of the network (i.e., the hidden/output state $\mathbf{h}_{t-1}$ and the cell state $\mathbf{c}_{t-1}$) and the next time step of the data sequence to compute the output and the updated cell state $\mathbf{c}_t$.

Figure 3. 14. The information flow through LSTM-RNN



Two types of 6-layer LSTM networks are proposed for classification in the MATLAB application, as illustrated in Figure 3.15. Generally, the network starts with a sequence input layer followed by a (Bi)LSTM layer which learns long-term dependencies between time steps of sequence data and a dropout layer to help prevent overfitting with random dropout with probability 0.05. To predict class labels, the network ends with a fully connected layer, a softmax layer and a classification output layer. The size of the sequence input layer is set to be 4, equal to the number of features of the input data and the size of the fully connected layer is set to be 2, equal to the number of output classes. The sequence length does not need to be specified. For (Bi)LSTM layer, the number of hidden units is specified as 100, the output mode as 'last', the state activation function as 'tanh' and the gate activation function as 'sigmoid'. With the constant learning rate factors specified, other learnable weights of (Bi)LSTM layers are initialized as default, including input weights, recurrent weights and biases.

If we use the full sequence at the prediction time, a bidirectional LSTM layer in the network is chosen which learns from the full sequence at each time step by looking at the time sequence in both forward and backward direction (Schuster and Paliwal, 1997). If we are forecasting values or predicting one time step at a time, an LSTM layer is used instead by looking at the time sequence in the forward direction. In our study, these two types are both used for comparison purposes. Although the number of hidden neurons specified for both models is 100, the number of activation neurons for the bidirectional LSTM network is 200, as twice as its counterpart (Figure 3.16). The reason is that the state neurons presented in each hidden neuron of the bidirectional LSTM network must include both forward and backward states independent of each other to take into account input information from both past and future of the currently evaluated time point of prediction. Meanwhile, the regular LSTM network is only designed with forward neurons.

Figure 3. 15. The design of regular and bidirectional LSTM-RNN

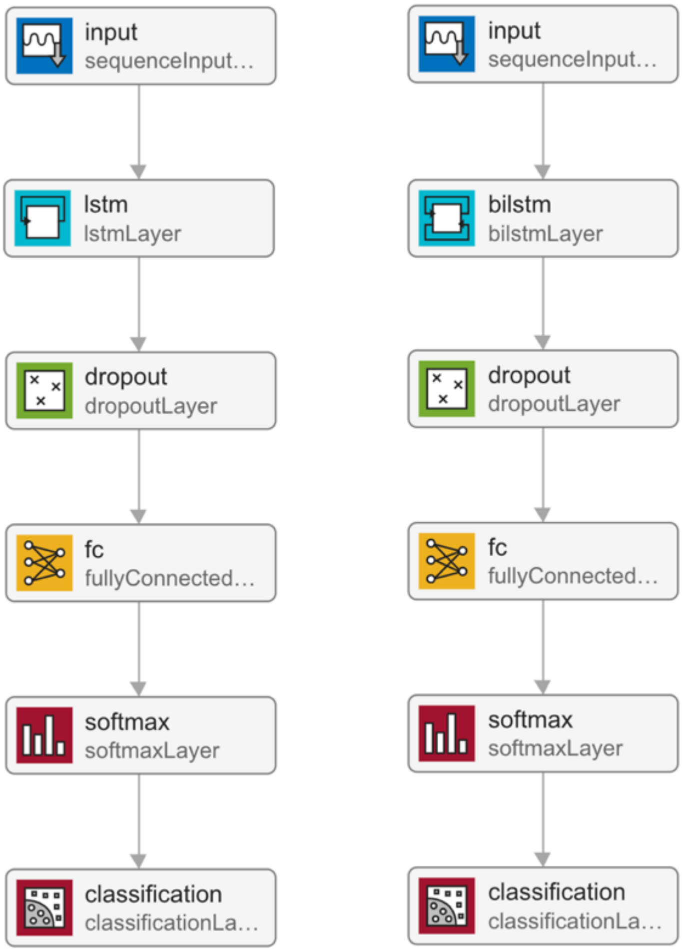


Figure 3. 16. The network analysis of regular and bidirectional LSTM-RNN

	Name	Type	Activations
1	input Sequence input with 4 dimensions	Sequence Input	4
2	lstm LSTM with 100 hidden units	LSTM	100
3	dropout 50% dropout	Dropout	100
4	fc 2 fully connected layer	Fully Connected	2
5	softmax softmax	Softmax	2
6	classification crossentropyex	Classification Output	2

	Name	Type	Activations
1	input Sequence input with 4 dimensions	Sequence Input	4
2	bilstm BiLSTM with 100 hidden units	BiLSTM	200
3	dropout 50% dropout	Dropout	200
4	fc 2 fully connected layer	Fully Connected	2
5	softmax softmax	Softmax	2
6	classification crossentropyex	Classification Output	2

3.3.3. Training and testing

Within the data set collected from driving simulation, 40 samples are randomly divided into 75% for training (30 samples), 15% for validation (6 samples) and 10% for testing (4 samples). Training data are presented to the network during training and the network is adjusted according to its error. Validation data are used to measure network generalization and to halt training when generalization stops improving. Testing data have no effect on training and provide an independent measure of network performance during and after training.

Feedforward Neural Network

Given an input X, a L-layer neural network performs the following computations to predict the class:

$$f_L(\theta_L, X) = f_{L-1}\left(\theta_{L-1}, f_{L-2}\left(\theta_{L-2}, \ldots, f_1(\theta_1, X)\right)\right)$$

, where f_i corresponds to the non-linearity applied at layer l_i. The process is also referred as feed-forward propagation in the deep learning literature. In our study, the network is trained with scaled conjugate gradient backpropagation which is a good choice for training pattern recognition network that its memory requirements are relatively small and it is much faster than standard gradient descent algorithms (MATLAB, 2020). Hence, given a certain number of known input-output, by iteratively taking a forward pass followed by backpropagation, the network values of the weights and biases are tuned to optimize the network performance. The performance function for FFNN is mean square error which is the average error between the network outputs and the target outputs. However, if the error on the training set is driven to a very small value, the problem of overfitting occurs which causes large error as new data is presented to the network. Therefore, the method for improving generalization called "early stopping" is used that the training is stopped when the error on the validation set begins to rise, indicating the network begins to overfit the training data, as shown in Figure 3.17. Also, because the system automatically initializes different weights and biases of the network for training and randomly allocates different samples into training, validation and test sets, different results can be found with the same input data and retraining multiple times is needed to ensure that a neural network of good accuracy has been achieved.

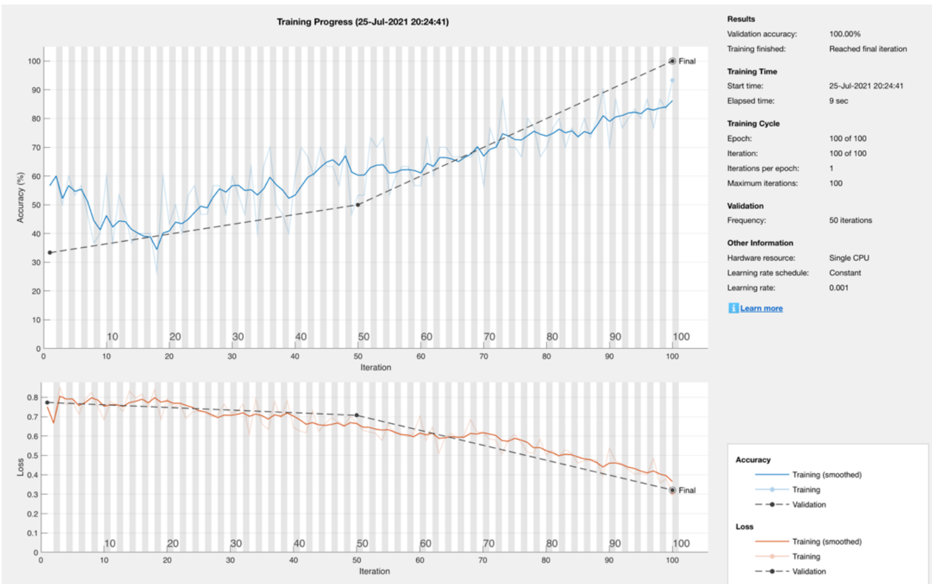
(Bidirectional) Long Short-Term Memory – Recurrent Neural Network

The training options are specified as follows: the solver set to be the adaptive moment estimation (i.e., 'adam') which is suggested to work best with RNNs (MATLAB, 2020), the gradient threshold to be 1 and the maximum number of epochs to be 100 to allow the network to make 100 passes through the training data. Because the data set is small with short sequences, the training is better suited for the CPU as specified in the 'ExecutionEnvironment'.

Figure shows an example of training accuracy and loss subplots during training progress across all iterations. When the training progresses successfully, the accuracy value eventually increases towards 100% while the cross-entropy loss value decreases towards zero. If the training is not converging but oscillating between values, changing the training options such as decreasing initial learning rates may help the network learn better although it might result in a longer training time. Each training in our study may take about 10 seconds and several trainings are needed to achieve best results. The training process is set and executed using written commands on MATLAB's command window.

Figure 3. 17. Training performance in FFNN

Figure 3. 18. Training performance in LSTM-RNN

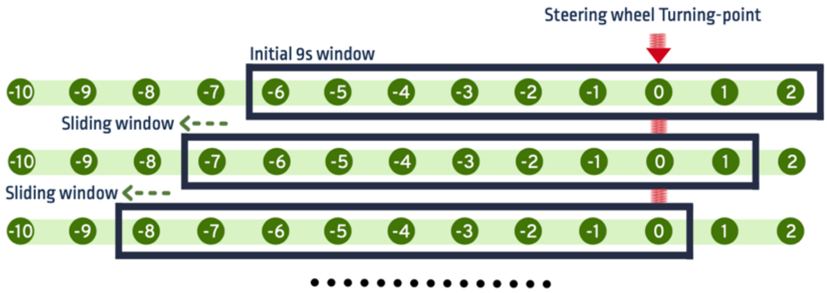


3.3.4. Further testing with naturalistic data

Firstly, general performance of the FFNN, LSTM-RNN, Bi-LSTM-RNN models on inference accuracy is compared using the full testing sequences collected from naturalistic driving which are completely independent datasets from training datasets. The results of testing accuracy are visualized by confusion matrices.

Secondly, the prediction performance for three models is evaluated using the sliding window method which is a temporary approximation over the actual value of the time series data (Yahmed et al., 2015). Specifically, the intention is inferred every 1s before the manoeuvre as the testing sequence of 9-second window is shifted back for every 1s, as illustrated in the Figure 3.19. The process will be continued till time series data of its initial 9s window is exhausted. In this method, more data in many previous time steps need to be extracted and pre-processed in the same way as previously described.

Figure 3. 19. Illustration of the sliding window method



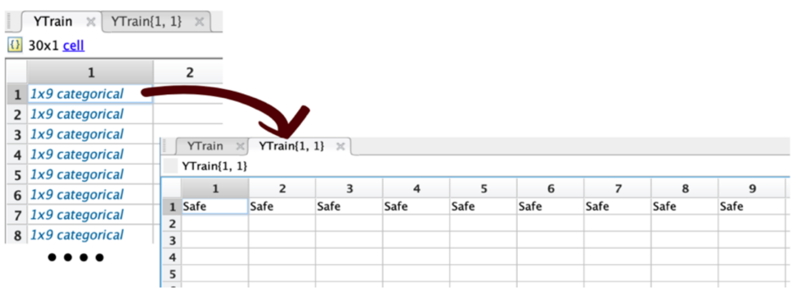
Thirdly, using the same sliding window method, models are trained with only 3 input variable, one time without the steering wheel feature and another time without the speed feature. The aim is to compare the variable importance between these two features in contributing to the prediction accuracy of the model trained with full input features.

Next the models are trained with completed sequence data while, at the testing step, the testing data are cropped to predict partial temporal sequences. The aim is to compare the sensitivity of models to the partially observed dataset. In LSTM-RRN, testing data of certain number of time steps is simply cropped, leaving empty cells. However, in FFNN, empty cells in testing sequences are not accepted. Here the data that are desirably cropped can be replaced with "NaN" text (i.e., "not a number"). In this method, the models are also trained three times, one with full input features, one without the steering wheel feature and one without the speed feature.

Finally, the real-time intention inference with the Bi-LSTM-RNN model is presented. Hence, the model is trained in terms of sequence-to-sequence classification rather than sequence-to-label classification as done in previous methods which requires the output mode in the neural network set to be "sequence" rather than "last". Also, the training output YTrain needs to be reformatted as a cell array of categorical sequences as shown in Figure 3.20. The testing output must be rearranged in the same manner and the testing dataset is also expanded about 12s before and 5s after the heading angle turning-point to simulate the whole inference cycle for an overtaking manoeuvre.

Generally, all the training results at each time step for each type of models are recorded in Excel to ultimately visualize these results using graphs.

Figure 3. 20. The data pre-processing in sequence-to-sequence classification



Chapter 4: Analysis results and discussion

4.1. Results

4.1.1. Description

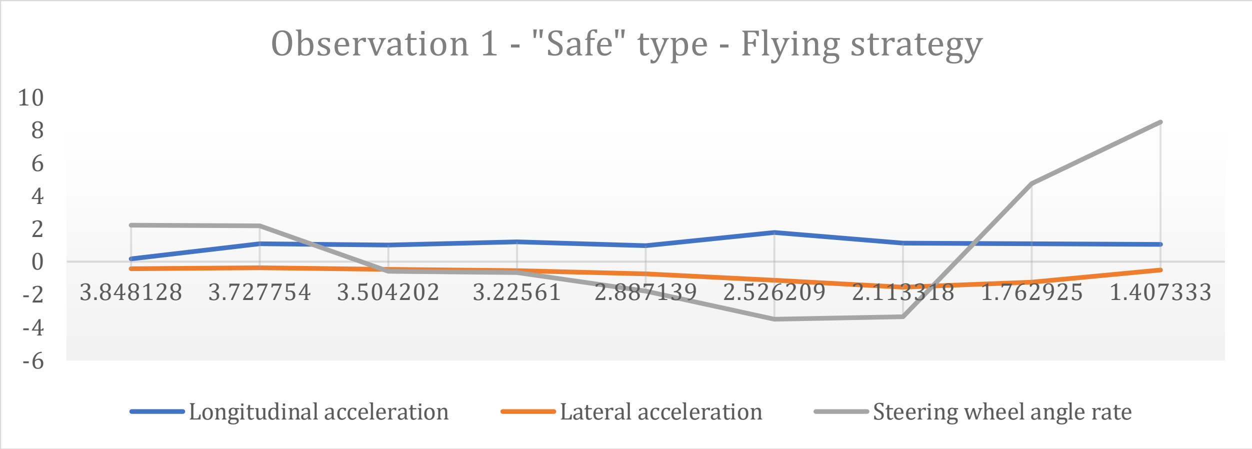
The next 2 pages illustrate safe and dangerous overtaking, extracted from simulation driving. The first observation for each type represents the flying overtaking style and the remainder the accelerative overtaking style. The first graph in one observation maps three features including longitudinal acceleration, lateral acceleration and steering wheel angle rate, all against the headway measure on the horizontal axis and the second graph show the vehicle speed also against the headway measure. The lateral acceleration measure used in this part is for clarification purposes but will not be used in the model training. Generally, from 4 observations in Figure 4.1 & 4.2, the road section designed in the simulation seems to have a slight right-curve before a straight road with an overtaking opportunity. Hence, in most cases, the steering wheel angle rate is negative, right before a sharp increase into a large positive rate when starting overtaking. Noticeably, it takes up to 2 seconds after the steering wheel turning point to observe the lateral acceleration to start increasing. This finding explains the 9-second framework chosen in our study which expands 2 seconds after the steering wheel turning point and still makes the prediction useful. In flying overtaking, the longitudinal acceleration line is positive all along the time and the vehicle speed smoothly increases over the timeframe. In contrast, the longitudinal acceleration line in accelerative overtaking either equals zero or drops into a negative value at some point before soaring back to a large positive value and the speed line adjusts accordingly. However, the speed choice for overtaking varies much. The steering wheel turning points must be at the headway value equal or larger than 1.2 to be classified as “safe” which is the only clear difference between two Figures.

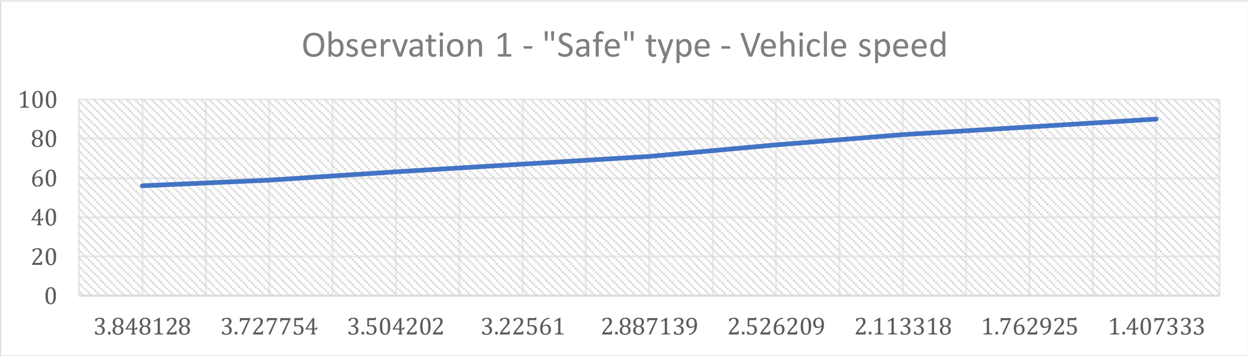
Table 4.1 shows the distribution of two overtaking styles by safety categories. The driver in this experiment seems to prefer accelerative overtaking which accounts for 60% (24/40) in total 40 overtaking manoeuvres. Interestingly, the shares of dangerous overtaking in both flying and accelerative overtaking strategies are relatively equal with 43.8% and 50% respectively. This means that either the driver overtakes at his desired speed without car-following in the flying style or adjust his speed to follow the preceding vehicle before overtaking in the accelerative strategy, he will have the same chance of violating the headway rule. The explanation is that both the task of restraining over-speeding in flying overtaking and the task of maintaining a safe gap in car-following process of accelerative overtaking are equally difficult.

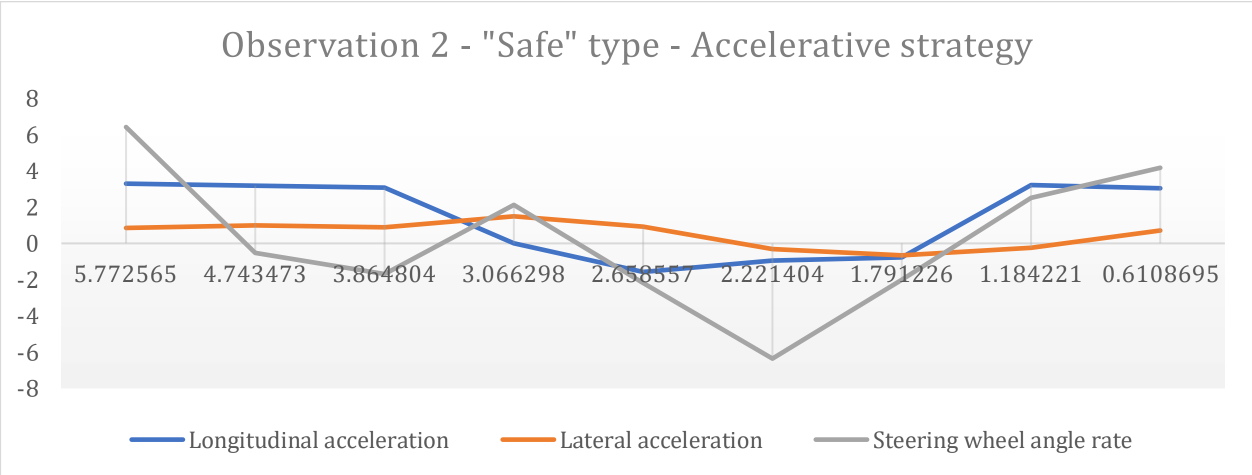
Table 4. 1. Distribution of overtaking styles by safety in simulation driving

Category	Flying	Accelerative	Total
“Safe”	9 (56.2%)	12 (50%)	21 (52.5%)
“Dangerous”	7 (43.8%)	12 (50%)	19 (47.5%)
Total	16 (100%)	24 (100%)	40 (100%)

Figure 4. 1. Observations of safe overtaking in simulation driving







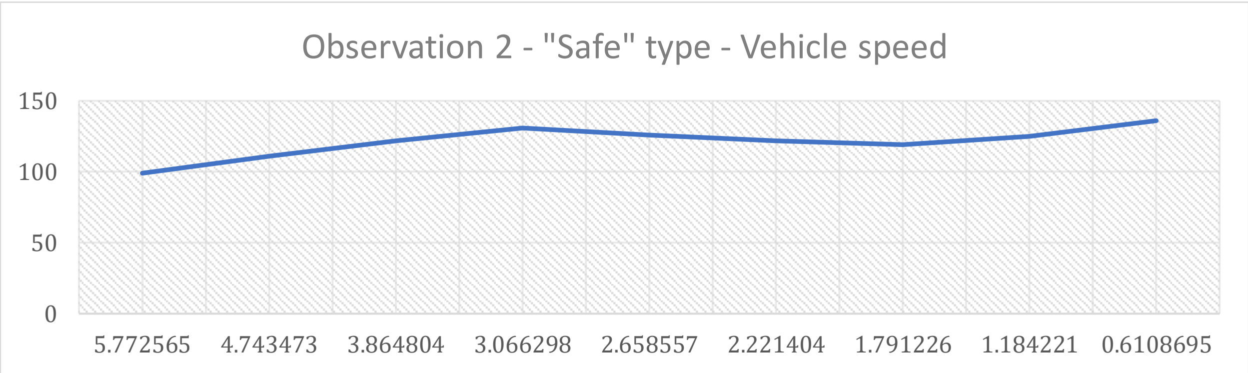
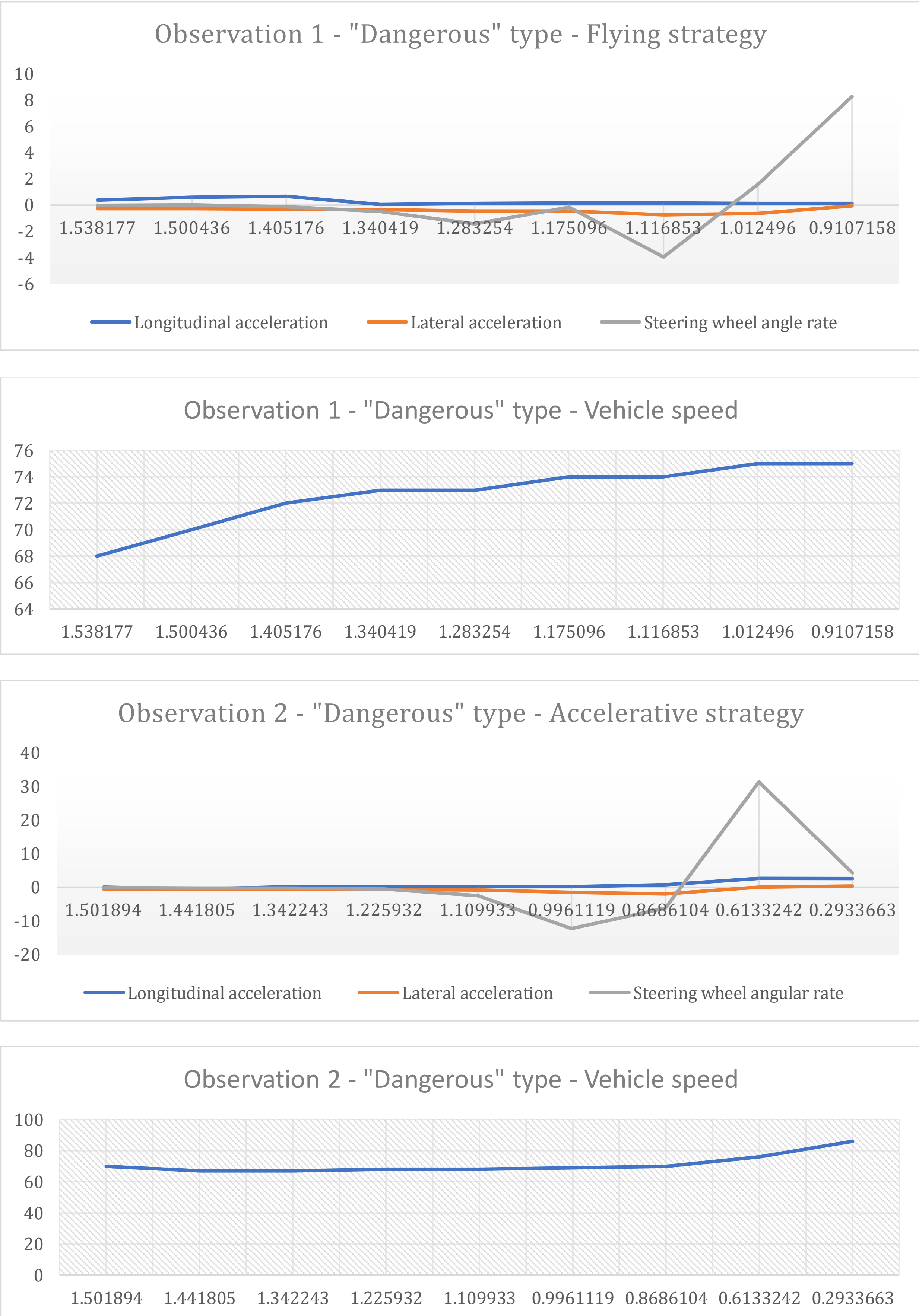


Figure 4. 2. Observations of dangerous overtaking in simulation driving



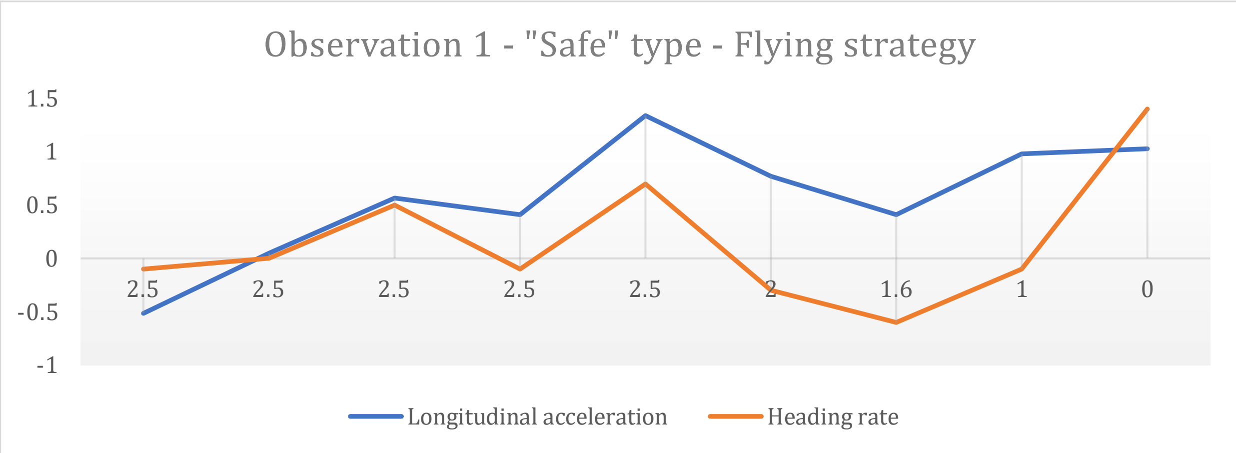
Similarly, observations from naturalistic driving are presented in the next 2 pages with the same structure described in the previous part. However, the lateral acceleration measures are absent and the steering wheel angular rate is replaced by the heading angular rate. The features of flying and accelerative overtaking with respect to longitudinal acceleration and speed variables are quite similar to observations found the simulation dataset. Given all overtaking is taken on the straight road, the small fluctuation in heading rate lines in all the graphs indicates the vehicle's lateral adjustments towards the road centre before the lateral departure into opposing lane in the last 2 seconds of time window. The mean and standard deviation for each of 9 timesteps of four considered variables are further shown in the Appendix A- D.

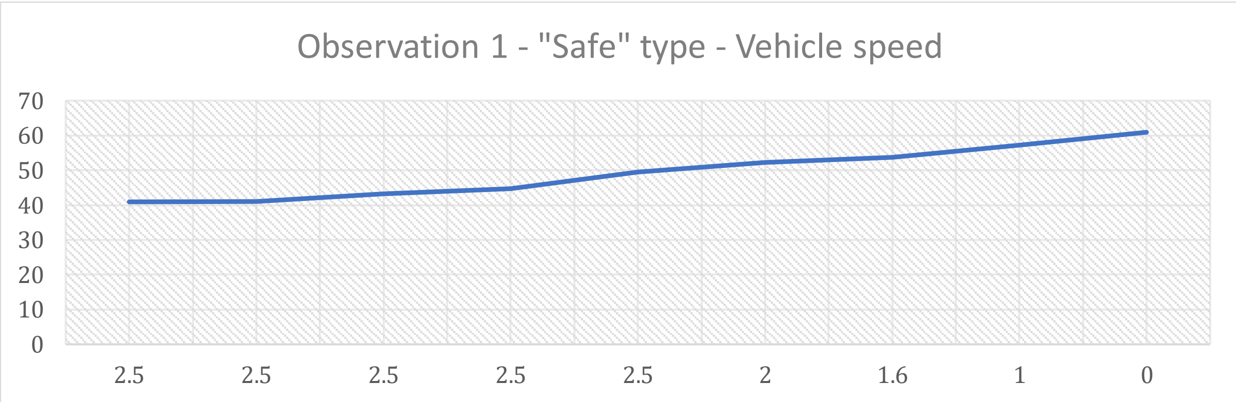
The Table 4.2 again shows the distribution of two overtaking styles by safety categories. The driver in real-world environment also prefers accelerative overtaking which accounts for 64.3% (18/28) in total 28 overtaking manoeuvres. This finding was already confirmed by Wilson & Besta (1982) and Hegeman et al. (2008) that the accelerative strategy in overtaking is mostly used by the driver. The chances of being classified as "dangerous" are relatively equal in both flying and accelerative overtaking styles, with 70% and 72.2% respectively, again stating that the latter should not considered safer than the former. In fact, based on t-tests, it is also found that there is statistically no significant difference in the headway at the turning point of steering wheel between two overtaking strategies in both simulation dataset (t = 0.027, significance level = 0.05) and naturalistic dataset (t = -0.274, significance level = 0.05). However, the only noticeable difference between simulation and naturalistic dataset is the much higher chance (64.3%) of not keeping the safe headway in real-world driving. Many manoeuvres in samples start rotating the vehicle to overtake at the headway smaller than 1s (i.e., the smallest value observed is 0.5s), leaving only 1s to reach the headway of zero as shown in Figure 4.4. Even in safe overtaking as indicated in the 1st observation in Figure 4.3, the driver leaves only 2s to reach the preceding vehicle after the heading rate turning-point. In other words, the overtaker had not even totally crossed the centre line at the moment the front of the vehicle is next to the preceding vehicle. Statistically, it is found that headway at the start of overtaking in simulation driving is significantly larger than this value in naturalistic driving (t=2.68; significance level = 0.05). This finding is in line with the study of Hegeman (2008) in which more than half of observed overtaking headways between passenger cars in the Netherlands were smaller than 1s. Compared to driving scenarios in simulation with few distant oncoming vehicles on the opposing rural lane, driving in urban areas face high opposing traffic volume, more likely forcing the driver to leave its own lane quite late and overtake on the opposing lane as quick as possible. The vehicle speed line in the 2nd observation in Figure 4.4 is horizontal before heading turning-point, indicating a long car-following period with a constant speed while waiting for an overtaking opportunity. SWOV (2012) also agreed that the average headway times are often smaller on busy roads than on quiet roads and rear-end collision take place more frequently when traffic is busy.

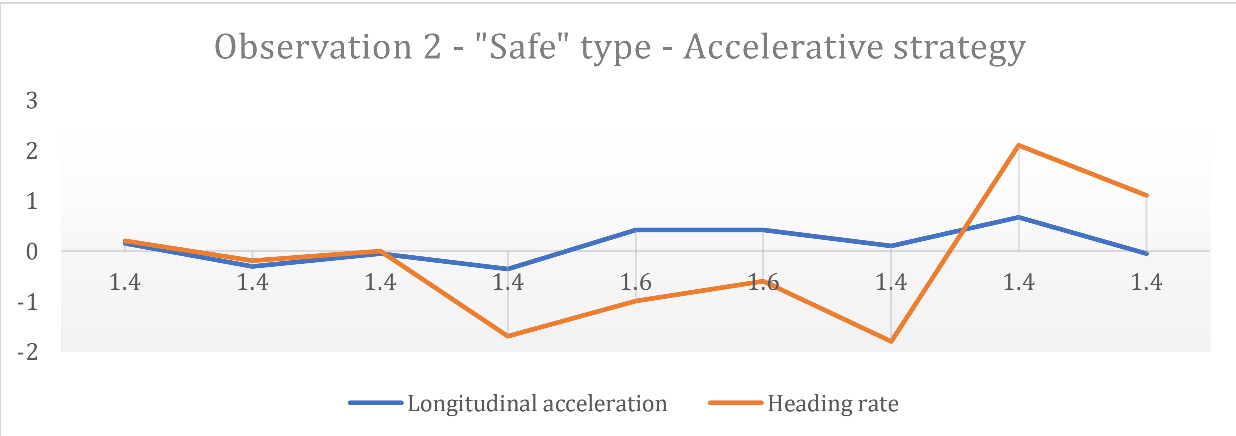
Table 4. 2. Distribution of overtaking styles by safety in naturalistic driving

Category	Flying	Accelerative	Total
"Safe"	3 (30%)	7 (38.9%)	10 (35.7%)
"Dangerous"	7 (70%)	11 (61.1%)	18 (64.3%)
Total	10 (100%)	18 (100%)	28(100%)

Figure 4. 3. Observations of safe overtaking in naturalistic driving







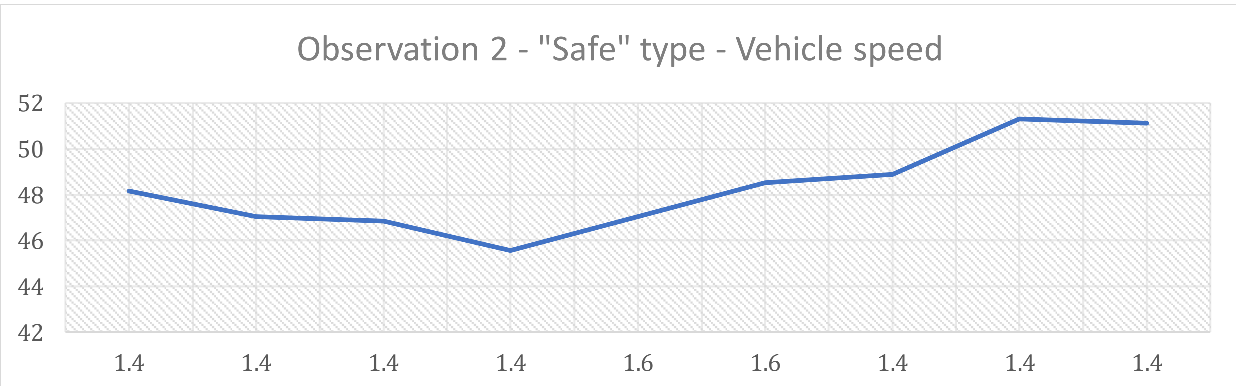
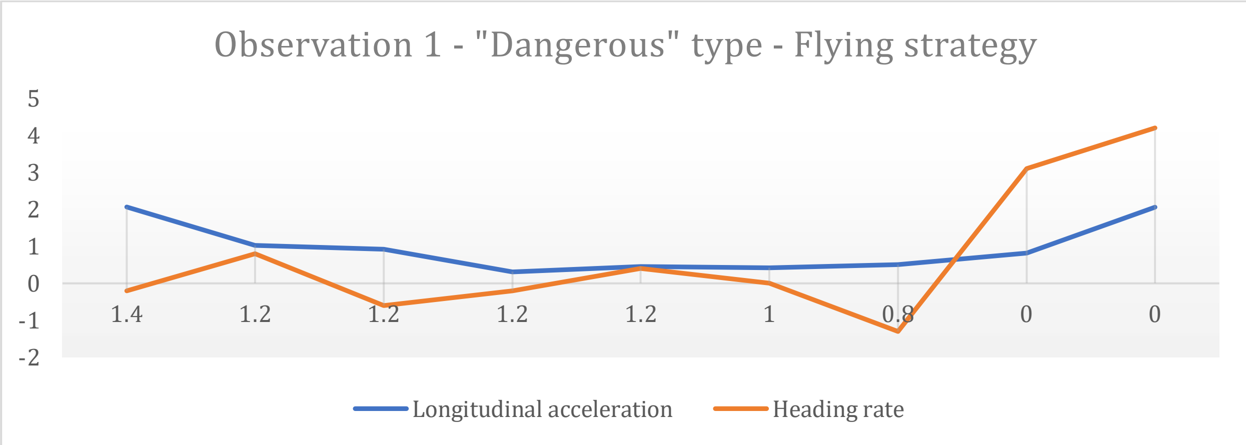
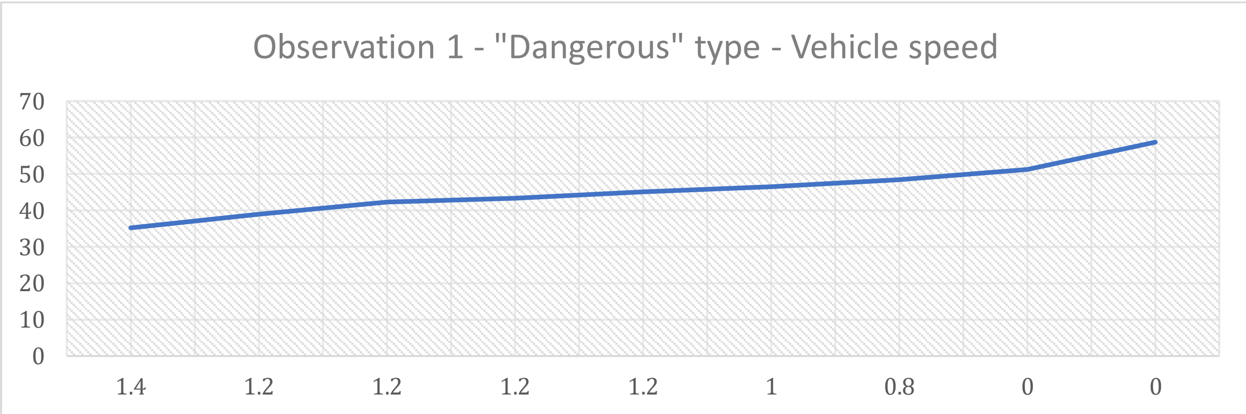
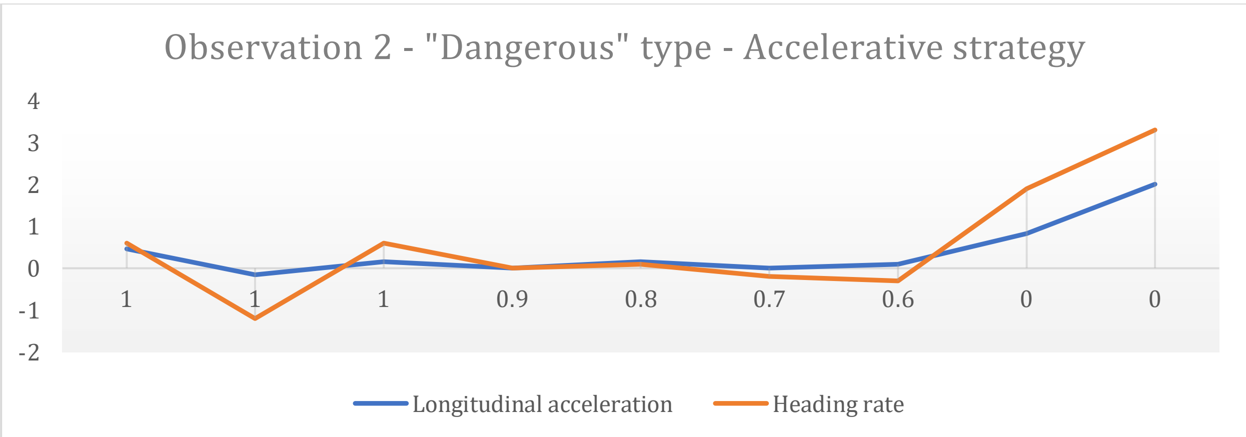
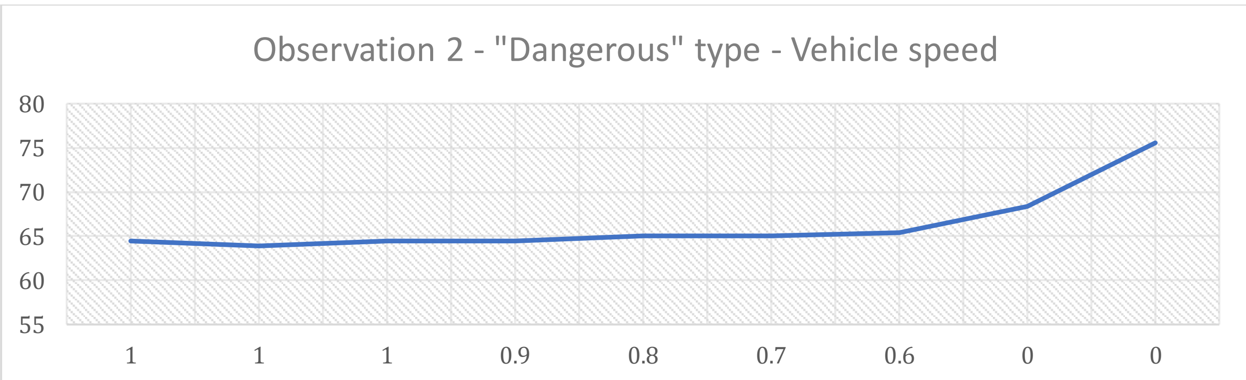


Figure 4. 4. Observations of dangerous overtaking in naturalistic driving





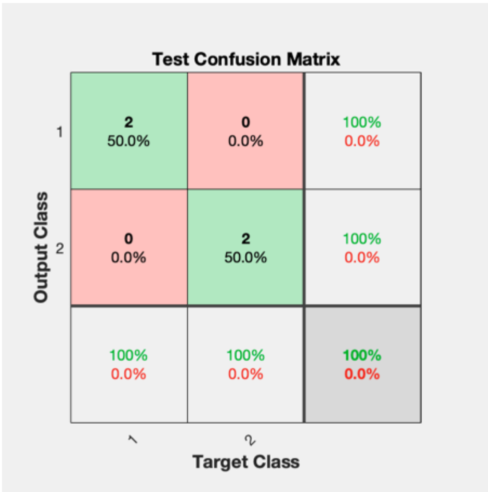


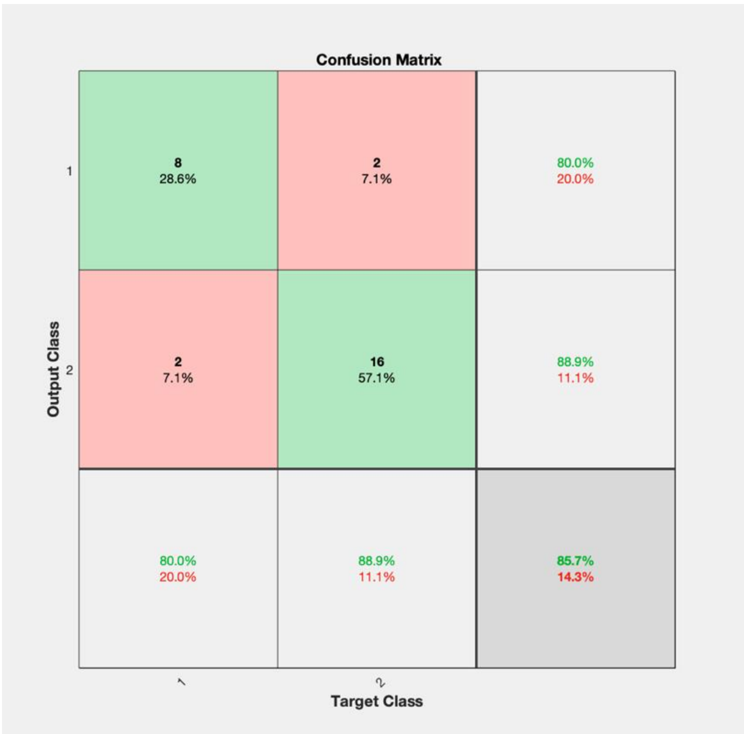


4.1.2. Results of Feedforward Neural Network (FFNN)

The confusion matrix shows the true positive, false positive and false negative counts. Class 1 and 2 represents the "Safe" and "Dangerous" categories respectively and the target and output classes as ground-truth and predicted classes respectively. For each class, the true positive counts are displayed on the diagonal. The top subplot in the Figure 4.5 shows the results of testing the trained FFNN model using 04 samples taken from simulation dataset, in which 100% of ground-truth "Safe" signals are correctly classified as output class 1 and 100% of ground-truth "Dangerous" signals are correctly classified as output class 2, resulting the overall accuracy of 100%. However, when further testing the trained model using naturalistic dataset indicates the overall prediction accuracy of 85.7%, as shown in the second confusion matrix. Specifically, 80% of the signals classified as "Safe" are actually safe and 88.9% of the signals classified as "Dangerous" are actually dangerous.

Figure 4. 5. Confusion matrix of FFNN testing





4.1.3. Results of Long Short-Term Memory – Recurrent Neural Networks

Figure 4.6 and 4.7 indicate confusion matrices of LSTM-RNN and Bi-LSTM-RNN testing respectively. The left subplots in each Figure show model testing results using simulation testing samples kept aside before, which indicates a prediction accuracy of 100% (4/4) in both models. However, when testing these models using naturalistic dataset, the Bi-LSTM-RNN model achieves a better prediction performance with the overall accuracy of 92.86% (26/28), as compared to 89.29% (25/28) in the regular LSTM-RNN model. In the Bi-LSTM-RNN model, 94,4% (17/18) of dangerous overtaking is correctly predicted and 90% (9/10) of safe overtaking is correctly recognised while in the regular LSTM-RNN model, the corresponding numbers are 100% (18/18) and 70% (7/10) respectively.

It is understandable that testing samples taken from naturalistic driving achieves a lower prediction accuracy than testing samples taken from the same training sources. Different driving environment and drivers' driving styles may be some obvious explanation. For example, while the speed of preceding vehicle in simulation is designed to keep constant, this speed is dynamically changing in real-world which may affect the internal prediction of headway in trained models. Meanwhile, the classification criterion critically depends on the headway measure. In general, these two kinds of LSTM-RNN models perform better than the FFNN model described before. This finding is in line with the work of Yang et al. (2020) and Schuster et al. (1997). The RNNs with LSTM units are very expressive models with an internal memory to allow them to model the much needed long temporal dependencies for prediction.

Figure 4. 6. Confusion matrix of LSTM-RNN testing

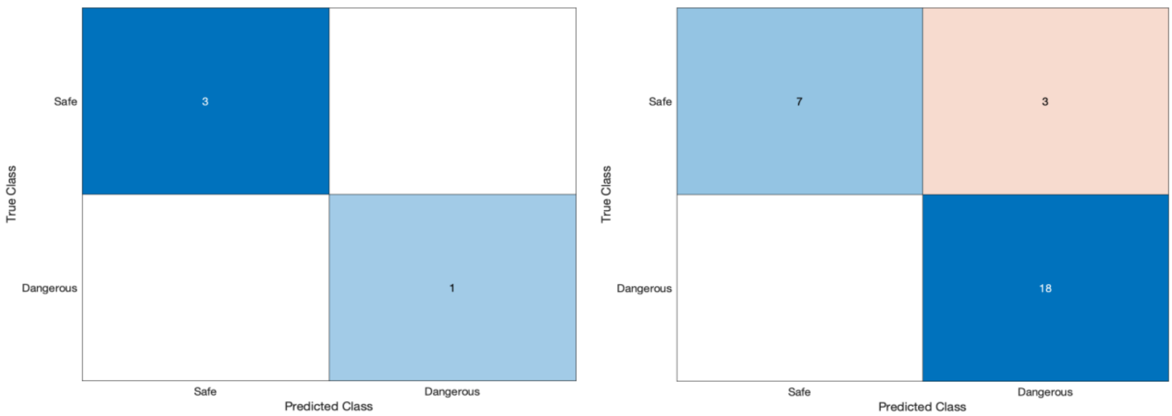
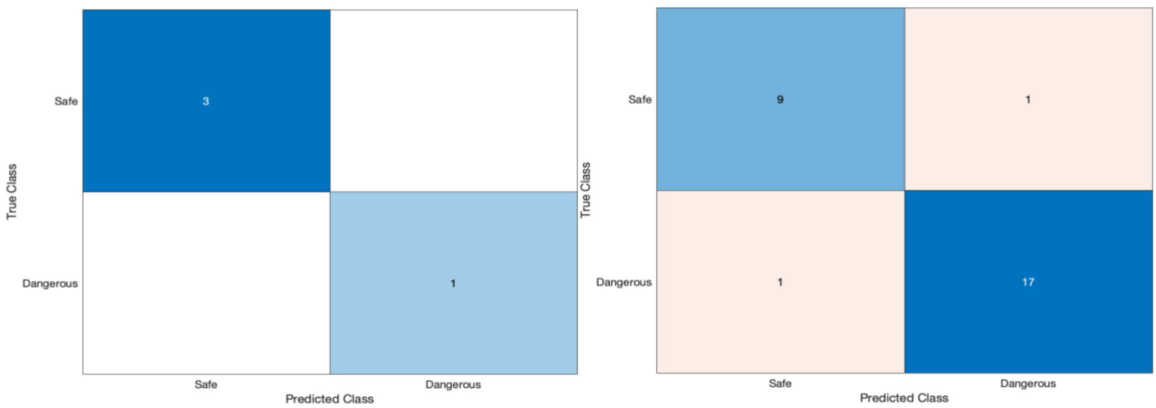


Figure 4. 7. Confusion matrix of Bi-LSTM-RNN testing



4.1.4. Comparisons between neural networks

Figure 4.8 illustrates the model prediction performance of FFNN and RNNs using the sliding window method. The upward trends in prediction lines for all considered models means the less error approximation is achieved when sliding the time window closer to the overtaking event. The Bi-LSTM-RNN based method generally achieved the most accurate results, followed by the regular LSTM-RNN and FFNN based methods. This can be explained that while the FFNN approach performs a simple fusion by concatenating input feature vectors, RNN-approaches use a fully connected layer to fuse the high-level representations at each time step, capturing temporal contexts. This form of sensory fusion is more principled since the sensor streams represent different data, ultimately resulting in better performance. Specifically, the LSTM-based approaches are more accurate than the FFNN-based model when predicting the overtaking safety since the turning point of heading rate. In contrast, the FFNN model gives a more robust detection of dangerous overtaking than the other two methods when the safety is predicted more earlier. This may be explained by the fact that as the testing sequence move earlier, the RNN model is confused with more irrelevant information involved in the temporal sequence. On the other hand, the FFNN model is trained with the statistic features of sequence which allows the network to still be able to capture the significant features within the temporal sequence.

Figure 4. 8. Prediction accuracy using the sliding window method

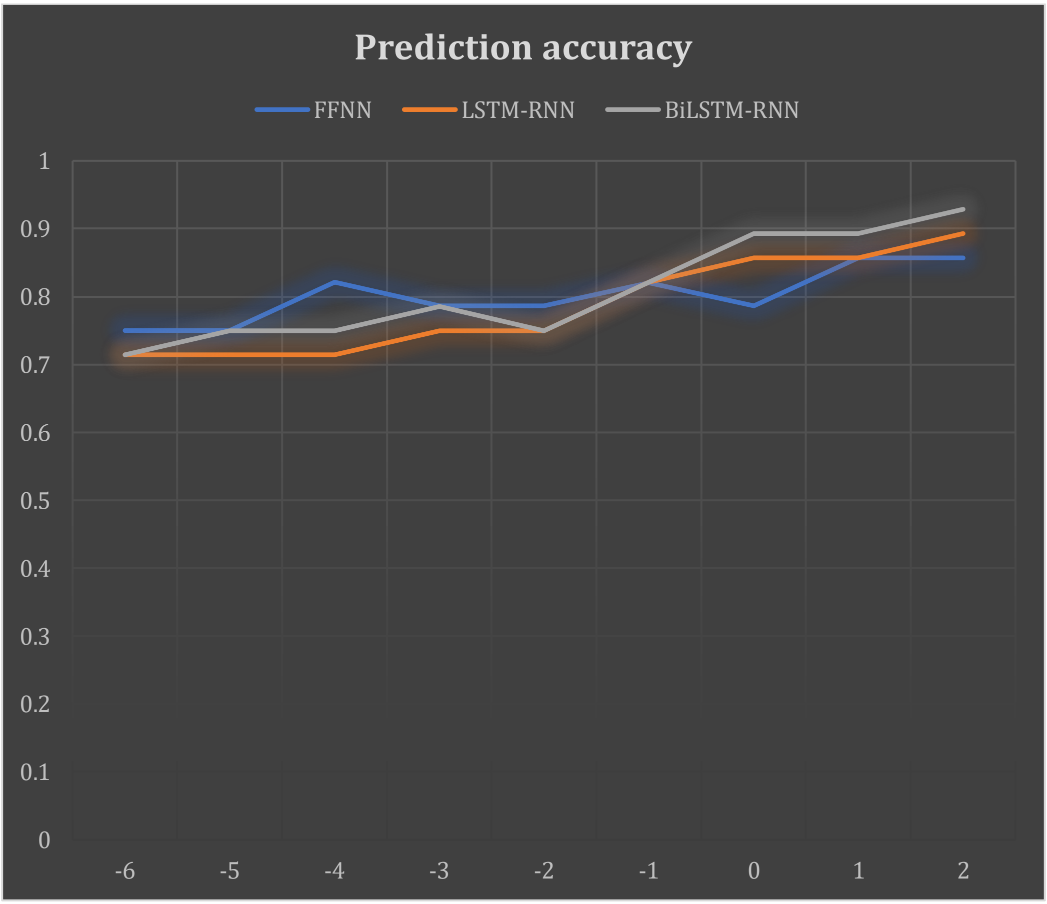
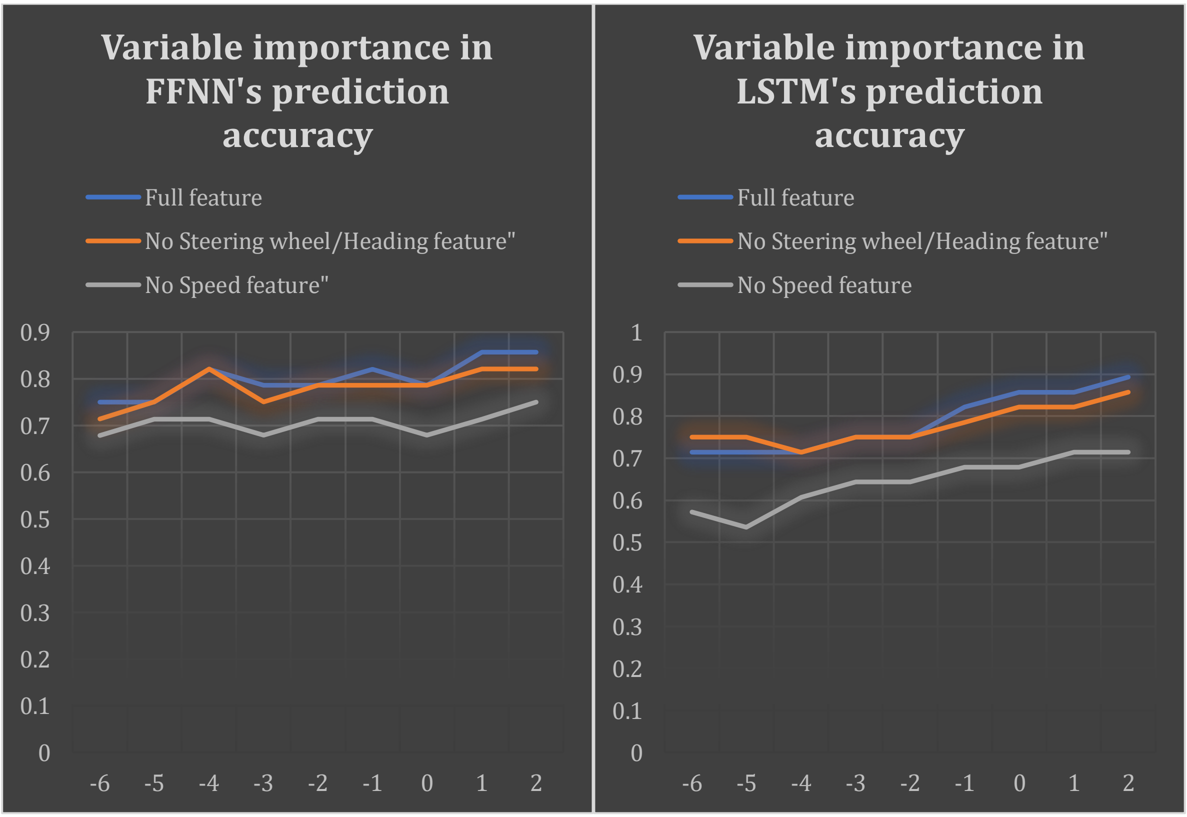


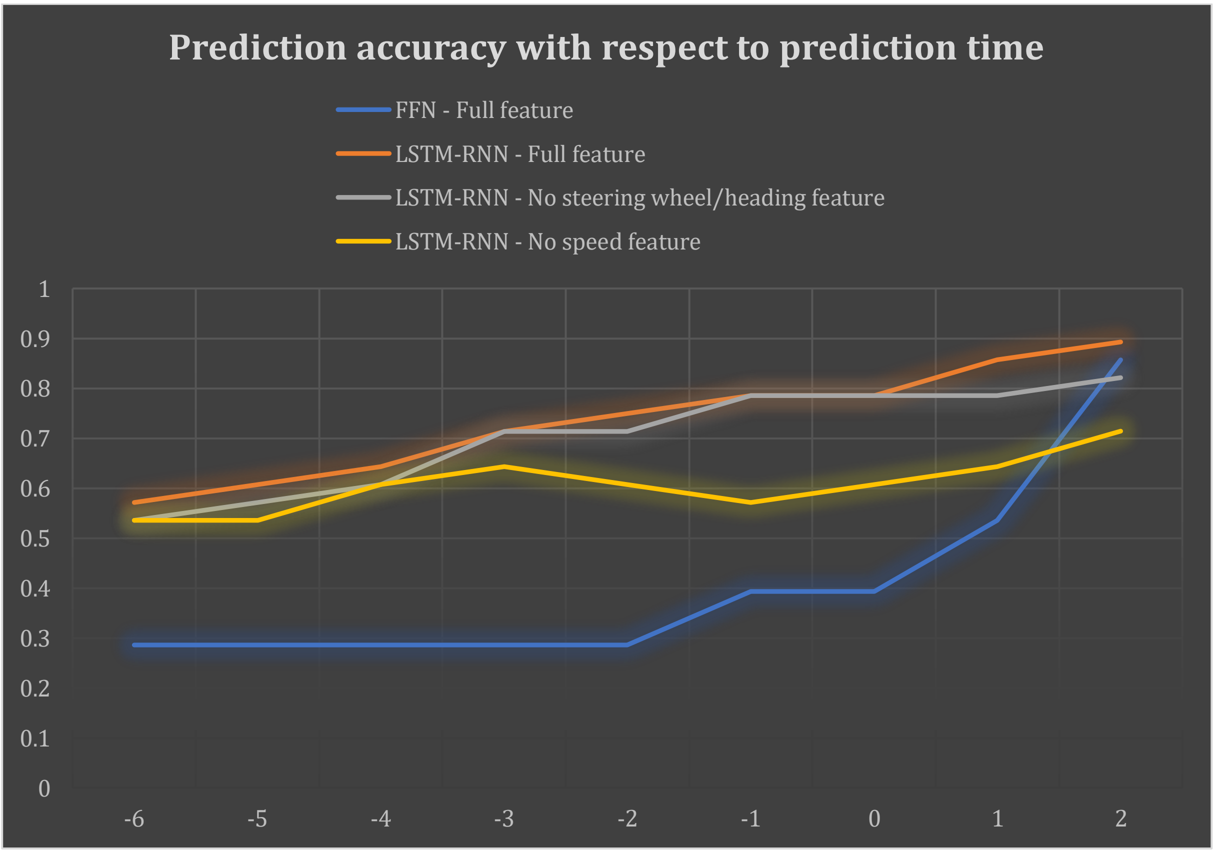
Figure 4.9 includes two subplots showing the importance of steering wheel/heading and speed features in contributing to the prediction performance of FFNN and LSTM-RNN based models respectively. Based on results from these two different methods, the longitudinal speed information significantly contributes to the prediction performance. The trained models without the speed as a variable input achieved much lower accuracy than the models with full feature vectors despite that these models are still trained with the longitudinal acceleration variable – a very relatable variable to the speed. In contrast, the trained models without the consideration of steering wheel/heading features achieved only slightly lower accuracy than the models based on full input feature vectors, indicating a small impact of steering wheel/heading feature on prediction performance. Besides, this small impact can only be clearly observed from the steering wheel/heading angular rate turning-point onwards. In the second subplot, exclusion of steering wheel information in training LSTM models even makes the prediction performance better when inferring safety early. The reason may be that there are no significant characteristics of the steering wheel feature in temporal sequence if the time window is captured way too early from the steering wheel angular rate turning-point. Bi et al. (2015) constructed the model to detect the normal lane change and emergency lane change manoeuvres and agreed that the steering wheel angle signal as the only input into the algorithm cannot help infer the driver manoeuvre at a very early stage or before the manoeuvre happens.

Figure 4. 9. Variable importance in prediction accuracy



In order to predict in a useful way, an algorithm must learn to predict the future given only a partial temporal context which makes anticipation challenging and also differentiates it from activity recognition. Previous works (Koppula and Saxena, 2013; Morris et al., 2011; Ryoo, 2011) train discriminative classifiers (such as Support Vector Machine or Conditional Random Field) on the complete temporal context but at test time predictions are made within a filtering framework due to only observing a partial temporal context. Figure 4.10 illustrates the prediction performance with respect to the prediction time by observing partial temporal context. As the testing sequence getting smaller, more important characteristics of input features will lose along with shorter overtaking preparation duration. The orange, grey and yellow lines respectively represent prediction results given by LSTM-RNN models with full feature vectors, without steering wheel feature and without speed feature. Again, the speed feature is more important than the steering wheel feature in improving prediction performance. Without speed feature, the trained LSTM-RNN model can only achieve the maximum accuracy of 71,43%. The LSTM-RNN based model with full input feature can 80% accurately predict dangerous overtaking at 1s before the turning point of heading angular rate which gives sufficient time to react (i.e., either reducing speed or quickly turning the steering wheel if overtaking opportunity perceived). In addition, prediction results given by the FFNN model are represented by the blue line in which the accuracy drops more rapidly as the testing sample getting smaller, showing a more sensitivity to the partially observed datasets of the FFNN model which is not a sequence-based method. In contrast, prediction models with a recurrent architecture which unfolds through time let us train a single classifier to learn to better handle partial temporal context of varying lengths.

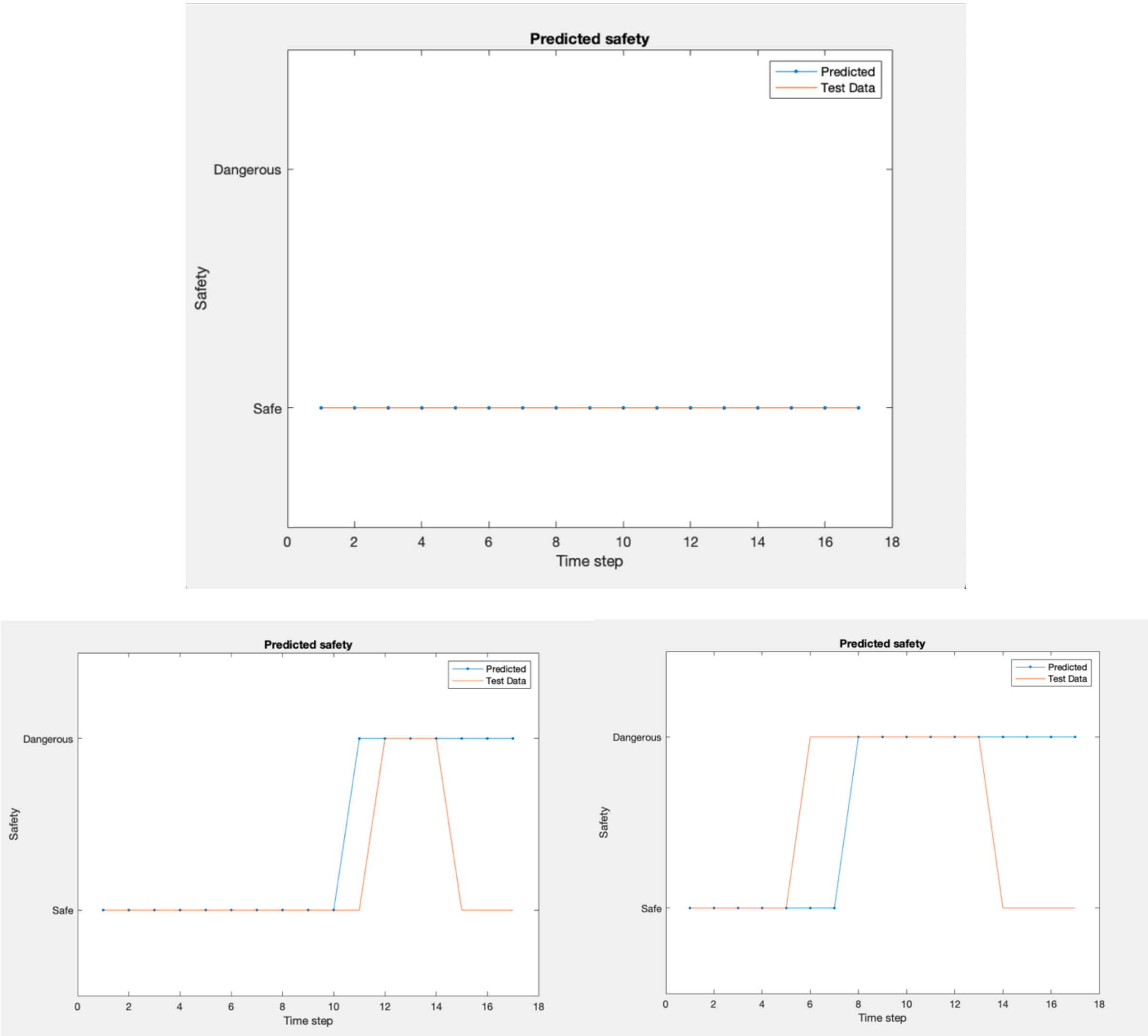
Figure 4. 10. Prediction accuracy with respect to prediction time



4.1.5. Real-time inference

Figure 4.11 illustrates examples of the real-time safety prediction with the Bi-LSTM-RNN model. In the training process, the point of initiating dangerous overtaking is manually selected as the point of headway value reaching 1.2 before the turning point of steering wheel angular rate and the finished point of prediction is determined as the moment when the vehicle is just crossing the lane (i.e., presumably 2s after the turning point of steering wheel angular rate). The top subplot represents a safe overtaking and the bottom subplot as dangerous overtaking. The Figure 4.11 shows that the LSTM-based system can efficiently detect the dangerous overtaking at 1-2s early before the headway feature reaching the critical value of 1.2. Noticeably, as the RNN models take the sequence data as inputs, the safety prediction signal can still be generated even after the vehicle has crossed the lane. This can be a concern in the real-world if the model is integrated with the Lane Departure Warning system to capture the vehicle lane position feature for model accuracy improvement. However, our main study objectives are to concentrate on the fast and early prediction for dangerous overtaking only which is more important than the status recovery issue.

Figure 4. 11. Real-time safety prediction of overtaking



4.2. Discussion

Our prediction model is trained in driving simulation based on the scenario of driving on rural roads but later tested in natural freeway and city driving with a relatively high inference performance. Also, between two considered overtaking strategies, only small differences are found in considered features in both datasets. Therefore, it would be possible to develop a single overtaking assistant, enabling assistance for these overtaking strategies and all drivers in different driving environments. Also, a questionnaire among drivers in 17 countries in the study of Hegeman (2008a) indicated that overtaking rules do not differ much which also enables international applicability of the overtaking assistant.

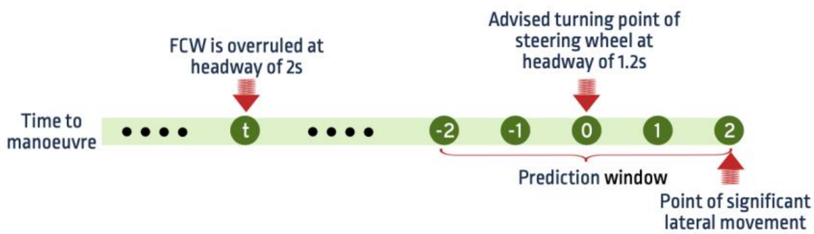
The model aims to predict dangerous overtaking which means a twofold task, including inferring overtaking intention first and then classifying its safety. As reported by Berndt et al. (2008), the turn signals are only used in 66% lane changes and less than 50% of the turn indicator activation happens in the initial phase of the lane-change manoeuvre. Therefore, it is not possible to rely on indicator usage for early overtaking intention inference and also the functioning of overtaking assistance system, as recommended by Lee et al. (2004). As a result, the overtaking assistant should be always switched on by the driver to perform effectively.

Existing driver assistance systems could have influence on the overtaking assistant, both in a positive and negative way. Hoedemaeker (1999) found that overtaking on two-lane rural roads is more dangerous when driving with Adaptive Cruise Control (ACC). Instead, proposed Forward Collision Warning systems (FCW) are more suitable to assist drivers to keep a safe following distance prior to overtaking, reducing the percentage of driving distance spent in rear-end collision mode up to 34 % (Regan et al., 2006). However, time headways at the start of overtaking manoeuvres as short as 0.5s are observed in our study while 2s is the recommended safe headway used in FCW. To avoid interfere by the FCW system before the overtaking assistant, the overtaking assistant should be integrated with the FCW in a way that once the early overtaking intention is recognised (i.e., speed acceleration), the FCW must be overruled and switched off automatically, as illustrated in Figure 4.12. Fairly short average perception-reaction time at the start of overtaking as of below 1s were observed (Lamm et al., 1999; Hegeman, 2008), confirming the fact that small headways as of 1.2s at the start of overtaking manoeuvres are likely to be less dangerous than during normal following conditions. In addition, a GPS and street map logger should be made use to extract a binary feature indicating if the vehicle is near a road artifact such as intersections, turns, hills … as seen in the work of Jain et al. (2015 & 2016) to help verify overtaking wish. More importantly, information about the vehicle's lateral lane position with respect to the lane markings possibly taken from Lane Departure Warning (LDW) signals should be used as inputs in training process as the lateral offset and lateral velocity are shown crucial in recognizing driver path planning intention in the work of Morton and Kochenderfer (2017). Li et al. (2016) also agreed with them that current prediction systems rely only on the driver control command such as the steering wheel angle and velocity which cannot provide an early intention prediction. In addition, vehicle-to-vehicle communication systems are being developed to inform drivers about sudden deceleration or swerving of preceding vehicles. In real-world, wrong predictions can still occur for different reasons such as signal loss of headways due to bad weather, failures in recognizing unmodeled events such as piggy overtaking, …

In terms of model building, information about vehicle dynamics and headway as the only measure of driving context are not sufficiently rich. The use of videos of the driver inside the car and the road in front may help improve prediction performance. While the road-facing camera outside the vehicle enables additional reasoning on manoeuvres (i.e., the presence of incoming traffic on the opposite lane, deviations of the preceding vehicles, traffic rules…), the driver-facing camera inside the vehicle provide head motion and facial landmark features. These are valuable inputs for overtaking intention inference system before any further safety classification tasks. In the study of Yang et al. (2020), they proved that the driver's intention can be early and roughly detected according to the driver's intended checking behaviours alone. Fortunately, significant advances have been made in the automobile industry in rich sensory integration such as radar for modelling the traffic, infra-red cameras for eye-tracking (Google, 2014; Wang et al., 2015) where our work can apply. However, Zhou et al. (2008) analysed driver eye movement to assess the cognitive distraction during lane-change preparation process and concluded that a secondary task could affect the intention prediction based on driver behaviour. Therefore, it is suggested that the prediction system based on driver behaviours needs to cooperate with the driver workload estimation module to achieve more accurate results (Xing et al., 2018b).

Looking back at the early study by Liu and Pentland (1997) who first employed hidden Markov model (HMM) and used only the vehicle status data such as the steering angle, steering velocity and the vehicle velocity to predict several driver intentions on a car simulator, an average of 88.3% detection rate was achieved after 0.5s when the action was initiated and they concluded that the vehicle status data are better used for intention recognition rather than intention prediction. In comparison, although our study uses the same limited number of vehicle status features, the LSTM-RNN based algorithm allows to predict the future given a partial temporal context with the accuracy about 80% at 1-2s before the significant change in steering wheel angle or 3s before the observation of significant lateral movement. With the much larger number of input signals inside and outside the vehicle, the RNN model in the study of Jain et al. (2015 & 2016) even achieved better prediction precision of 90%, can anticipate the manoeuvres 3.5s before they occur and outperformed over a range of different machine learning algorithms. This highlights the importance of modelling the temporal nature in the data for driver intention prediction. However, in prediction problems, there is an inherent ambiguity in which once the algorithm is certain about the manoeuvre type which exceeds the chosen threshold value, the question is that whether the system should predict immediately or wait for more information. For example, in situations where the driver aborts overtaking intention in the middle, different prediction strategies will result in different performance. This causes difficulties when manually labelling sequence-to-sequence classification. In our study chose, the earliest point for sending prediction signals is chosen as 2s before the turning point of steering wheel, as shown in Figure 4.12.

Figure 4. 12. Illustration of prediction model with respect to time-to-manoeuvre



Chapter 5: Conclusion

Most of traffic accidents are caused by human misbehaviours such as driver cognitive overload, judgement mistake and operation errors (Yang and Wang, 2007; Bellis and Page, 2008; Martinez et al., 2017). Driver assistance system (ADAS) products such as Lane Departure Warning (LDW), Adaptive Cruise Control (ACC) and Side Warning Assistant (SWA) which have been implemented on commercial vehicles, are treated as active safety systems despite that these functions interact with the human driver in a passive way which fails to monitor and understand the driver in real-time. Overtaking is one of the most dangerous and complex manoeuvres where the driver needs to be assisted the most with the help of ADASs.

Our study focuses on the preparation phase of overtaking before a significant lateral change to the left of the vehicle. The total of 40 and 28 legitimate overtaking manoeuvres were respectively recorded in simulation driving for model training, internal validation and testing purposes and in naturalistic driving in Hasselt city for further testing purposes. Four interested variables, including longitudinal speed, longitudinal acceleration, steering wheel/heading angular rate and headway between the driven vehicle and the preceding vehicle are extracted and interpolated. In this research, a sensory-fusion deep learning architecture based on Recurrent Neural Networks (RNNs) with Long Short-Term Memory (LSTM) units is proposed to monitor vehicle dynamics and driving context and predict dangerous overtaking manoeuvres with respect to rear-end collisions at 1-2s before the headway reaches its threshold of 1.2s with the performance accuracy of about 80%. This LSTM-RNN based system fuses multiple sensory streams from driving context and vehicle dynamics, models long temporal dependencies in a sequence-to-sequence prediction manner, learns to anticipate using only a partial temporal context and predict the dangerous overtaking before it is performed. The performance of three types of neural networks, including Feedforward shallow neural network (FFNN), regular LSTM-RNN and bidirectional LSTM-RNN are also compared and data pre-processing is required to build different input and output formats for training process in different neural network applications in MATLAB. Different from LSTM-RNN based methods which have a neural network layer for fusing the temporal streams of data coming from different sensors, the non-sequence-based method of FFNN uses a simple sensory approach of concatenation of feature vectors instead. The results are in line with previous works, showing that the Bi-LSTM-RNN based model outperforms in prediction performance because of its advantages in modelling temporal context and using all available input information in the past and future of a specific time framework for prediction. The study also found out that drivers are more likely to violate the safe headway rule in urban areas rather than in rural roads; changing the overtaking strategies does not help to increase the chance of avoiding rear-end collisions; speed is an important feature contributing to the early and accurate prediction while the steering wheel/heading feature only helps increase the prediction performance after their turning-points which can be used in manoeuvre recognition rather than prediction models.

In general, the study shows that although the model is trained in simulation with driving scenarios on two-lane rural roads, the model testing in natural freeway and city driving with the relatively high prediction accuracy regardless of overtaking strategies indicates a high possibility for model standardization.

5.1. Implications

In this study, short headway as of below 1s were often observed in real-world overtaking and drivers perform dangerous overtaking related to rear-end collisions at relatively same rates between accelerative and flying strategies. This calls for those responsible for enforcing regulations and providing driver training programs to increase drivers' awareness about the safe headway rule and practice regardless of their overtaking plans. Secondly, the study highlights the importance of driver intention inference in ADASs to actively warn the drivers about dangerous manoeuvres before they perform them. This importance is grounded in three reasons, including increased driving safety, increased mutual understanding between the human driver and the automation for the further construction of highly intelligent shared control strategies and contribution to a more naturalistic decision-making system for autonomous vehicles with human-like decision-making algorithms, making the intelligent vehicle much easier to be accepted by the public. Therefore, a more comprehensive understanding of the cognitive intention generation process according to the traffic context and driver behaviour is required before designing any prediction models. Thirdly, the fact that RNN-based models outperform other shallow neural networks in manoeuvre prediction indicates its power of capturing temporal context in improving prediction performance because it helps capture informative cues necessary for prediction which appear at variable times during preparation process for the manoeuvre. In addition, less sensitivity of the RNN-based models to partial temporal data allows the possibility of useful, acceptable and safe intervention at 1-2s before the headway reaches its critical value. Hegeman (2008) proved that the perception-reaction time defined as the time between passage of last oncoming vehicle and start movement to the left lane is fairly short, smaller than 1s. Therefore, the prediction window of 1-2s before the headway reaching its critical value in our study is more than sufficient for the driver to react. As speed feature itself was shown to largely contribute to prediction performance, the longitudinal acceleration can be used to overrule the Forward Collision Warning system which uses larger headway threshold for normal lane-following conditions and then the overtaking assistant takes control instead. In other words, integration with existing ADASs is necessary in implication phase. Finally, because the model was trained and tested in different driving environments by different drivers, it would be possible to develop a single overtaking assistant, enabling assistance for these overtaking strategies and all drivers in different driving environments.

5.2. Limitations and future research

Despite the promising results, this study has some limitations that should be considered in future research. The model in this study was constructed in a driving simulator experiment involving only one participant, more participants with diverse driving styles and experience should be invited in the experiment to achieve generalized results. Afshin et al. (2010) agreed with Clarke et. al (1998) that differences in overtaking manoeuvres are a function of not only driving experience but also driver age. Another limitation of the current study is linked to the realism of the driving environment, including (a) the preceding vehicle was driving with constant speed and (b) the same virtual driving environment was repeated, ignoring the variability of real-world road shapes and conditions. Farah et al. (2009) analysed drivers' passing decisions on 2-lane rural highways and found that one of the most important factors affecting the measurement of overtaking risk by drivers is geometric design. The sample size for both model training and testing less than or equal to 30 is indicated as "small", suggesting more overtaking manoeuvres that should be performed in the simulator as well as collected in naturalistic driving in different countries. Secondly, other safety concerns with respect to overtaking such as insufficiently large gap in the next oncoming traffic stream should also be taken into account to predict another class of dangerous overtaking. Hegeman (2008) stressed that estimating an overtaking gap to a next oncoming vehicle is fairly the most difficult but crucial subtask of overtaking in need of assistance which are not yet available. The reason is the difficulties with judging the speed of oncoming vehicles despite of reasonable estimates of the distance gap (Farber et al., 1967).

Theoretically, the prediction model should be based on the driver intention inference mechanism which requires three input modules, including road and traffic perception module, vehicle dynamic measurement module and driver behaviour recognition module. Therefore, to improve the model performance, not only vehicle dynamics and driving contextual information but also driver behaviour clues should be obtained from videos inside the car. This complex set-up for experiment needs further investments in future study. In the end, the challenge in further work still lies in modelling the temporal aspects of driving and fusing the multiple sensory streams in which the structure design and selection of training algorithm for the neural network is the heart of the prediction mechanism. Therefore, an ensemble learning-based method which combines three bi-directional LSTM-RNN models suggested by Schuster and Paliwal (1997) can be further investigated.

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Appendix A – Descriptive statistics of accelerative overtaking in simulation driving

Variable	Time step	Mean	Standard deviation
Speed	1	79.5	11.9818704
	2	79.2083333	13.7048997
	3	78.2083333	16.1836718
	4	78.875	18.2335393
	5	80.375	18.3464545
	6	81.8333333	16.8797967
	7	83.9166667	15.4636085
	8	88.9166667	15.8605792
	9	95.2916667	17.2412023
Longitudinal acceleration	1	0.17737422	1.13812235
	2	-0.2507159	1.49810259
	3	-0.1670662	1.502623
	4	0.23771207	0.76290353
	5	0.57846945	1.28634561
	6	0.39970589	1.1016112
	7	0.68898109	1.39313118
	8	1.91374226	1.38161695
	9	1.71303772	1.58478079
Steering wheel angular rate	1	-0.1375	3.12630664
	2	0.07299996	2.14141552
	3	0.17300004	2.42025169
	4	0.60799996	3.04708925
	5	-0.3265	2.91175747
	6	-3.175	5.30381689
	7	-3.399	4.55290479
	8	6.2215	7.20946246
	9	5.5245	4.82581642
Headway	1	2.41640497	1.4045321
	2	2.22567332	1.18949159
	3	2.07121914	1.01314345
	4	1.89716798	0.87581053
	5	1.78521987	0.64299152
	6	1.58220479	0.60268636
	7	1.35059058	0.57479045
	8	1.04651838	0.55136365
	9	0.70482651	0.53458255

Appendix B - Descriptive statistics of flying overtaking in simulation driving

Variable	Time step	Mean	Standard deviation
Speed	1	91.4375	30.0376847
	2	93.375	31.9434396
	3	94.8125	31.9900375
	4	95.6875	31.0198189
	5	95.625	28.3545999
	6	95.0625	24.0817185
	7	94.5625	21.3040489
	8	95.8125	20.295217
	9	97.5625	19.0996291
Longitudinal acceleration	1	0.58108328	1.17665885
	2	0.58203349	1.57927559
	3	0.49781576	1.11399423
	4	0.07756909	0.84815304
	5	-0.0789538	1.24439871
	6	-0.0934301	2.01288593
	7	-0.0641559	1.58296946
	8	0.74085606	1.37396744
	9	0.22051366	1.38890619
Steering wheel angular rate	1	-0.54225	2.59093022
	2	-0.44925	2.4710832
	3	0.22724994	0.68542972
	4	-0.5804999	1.2839056
	5	-0.3375	1.62794128
	6	-1.70925	2.42521937
	7	-3.20775	2.53993909
	8	5.87924988	4.69545647
	9	6.72975013	3.79238798
Headway	1	3.15556675	1.4419699
	2	2.7990565	1.11452426
	3	2.47744994	0.87482487
	4	2.19414816	0.73201134
	5	1.91677067	0.60126157
	6	1.6346633	0.5001112
	7	1.3462801	0.40687012
	8	1.04518299	0.3715237
	9	0.73862433	0.38584039

Appendix C - Descriptive statistics of accelerative overtaking in naturalistic driving

Variable	Time step	Mean	Standard deviation
Speed	1	49.1806	7.1406195
	2	49.1092	7.33003404
	3	50.364	6.022086
	4	50.0558	5.74971376
	5	49.634	6.00230878
	6	49.489	6.89311805
	7	50.3534	6.55073342
	8	52.1338	8.21296495
	9	55.231	10.6224946
Longitudinal acceleration	1	0.14861111	0.59408151
	2	-0.0198333	0.3320252
	3	0.34855556	0.75948444
	4	-0.0856111	0.5245711
	5	-0.1171667	0.40692639
	6	-0.0402778	0.5590679
	7	0.24011111	0.34940452
	8	0.49455556	0.79738213
	9	0.86033333	1.1363092
Heading angular rate	1	-0.0111111	1.45152613
	2	0.30555556	1.24213868
	3	1.579E-15	0.85954845
	4	0.41666667	1.10892104
	5	0.31666667	1.11526837
	6	0.01666667	0.94011889
	7	-0.4555556	0.91279933
	8	1.46111111	1.04269949
	9	1.53888889	1.72971908
Headway	1	1.27777778	0.22895043
	2	1.25	0.21760731
	3	1.21666667	0.20651164
	4	1.15	0.2093407
	5	1.14444444	0.23818486
	6	1.07777778	0.25101103
	7	0.92777778	0.28034759
	8	0.51111111	0.56764621
	9	0.33888889	0.50775039

Appendix D - Descriptive statistics of flying overtaking in naturalistic driving

Variable	Time step	Mean	Standard deviation
Speed	1	37.28016	11.296395
	2	38.85444	10.9480279
	3	42.28128	8.59883105
	4	45.39276	6.37650834
	5	49.33764	5.64763843
	6	51.6708	5.50357652
	7	53.67132	5.99993857
	8	56.57832	6.25156739
	9	60.17148	7.23625175
Longitudinal acceleration	1	0.1335	0.83162989
	2	0.571	0.74516575
	3	1.2349	1.11365629
	4	1.2604	1.4361481
	5	1.6154	1.60799483
	6	1.2963	2.10959101
	7	1.2142	2.03200147
	8	1.3631	1.84518084
	9	1.4972	1.27421381
Heading angular rate	1	0.92	6.25935744
	2	-0.53	2.16643589
	3	2.95	8.28361837
	4	-0.34	2.23218876
	5	-0.99	2.63542111
	6	-0.09	0.4954235
	7	-1.18	1.19703337
	8	1.38	1.96909455
	9	2.08	1.64370854
Headway	1	1.18	0.93903023
	2	1.42	0.7130529
	3	1.42	0.7130529
	4	1.48	0.5573748
	5	1.35	0.49721446
	6	1.2	0.34960295
	7	0.96	0.30623158
	8	0.49	0.45813632
	9	0.15	0.33747428