An Assessment System for Evaluation of Driving Competencies

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Experienced and novice drivers
Driver performance
Abstract

Automobiles have deeply impacted the way in which we travel but they have also contributed to many deaths and injury due to crashes. A number of reasons for these crashes have been pointed out by researchers. Inexperience has been identified as a contributing factor to road crashes. Driver’s driving abilities also play a vital role in judging the road environment and reacting in-time to avoid any possible collision. Therefore driver’s perceptual and motor skills remain the key factors impacting on road safety. Our failure to understand what is really important for learners, in terms of competent driving, is one of the many challenges for building better training programs. Driver training is one of the interventions aimed at decreasing the number of crashes that involve young drivers. Currently, there is a need to develop comprehensive driver evaluation system that benefits from the advances in Driver Assistance Systems. A multidisciplinary approach is necessary to explain how driving abilities evolves with on-road driving experience.

To our knowledge, driver assistance systems have never been comprehensively used in a driver training context to assess the safety aspect of driving. The aim and novelty of this thesis is to develop and evaluate an Intelligent Driver Training System (IDTS) as an automated assessment tool that will help drivers and their trainers to comprehensively view complex driving manoeuvres and potentially provide effective feedback by post processing the data recorded during driving. This system is designed to help driver trainers to accurately evaluate driver performance and has the potential to provide valuable feedback to the drivers. Since driving is dependent on fuzzy inputs from the driver (i.e. approximate distance calculation from the other vehicles, approximate assumption of the other vehicle speed), it is necessary that the evaluation system is based on criteria and rules that handles
uncertain and fuzzy characteristics of the driving tasks. Therefore, the proposed IDTS utilizes fuzzy set theory for the assessment of driver performance.

The proposed research program focuses on integrating the multi-sensory information acquired from the vehicle, driver and environment to assess driving competencies. After information acquisition, the current research focuses on automated segmentation of the selected manoeuvres from the driving scenario. This leads to the creation of a model that determines a “competency” criterion through the driving performance protocol used by driver trainers (i.e. expert knowledge) to assess drivers. This is achieved by comprehensively evaluating and assessing the data stream acquired from multiple in-vehicle sensors using fuzzy rules and classifying the driving manoeuvres (i.e. overtake, lane change, T-crossing and turn) between low and high competency. The fuzzy rules use parameters such as following distance, gaze depth and scan area, distance with respect to lanes and excessive acceleration or braking during the manoeuvres to assess competency. These rules that identify driving competency were initially designed with the help of expert’s knowledge (i.e. driver trainers). In-order to fine tune these rules and the parameters that define these rules, a driving experiment was conducted to identify the empirical differences between novice and experienced drivers. The results from the driving experiment indicated that significant differences existed between novice and experienced driver, in terms of their gaze pattern and duration, speed, stop time at the T-crossing, lane keeping and the time spent in lanes while performing the selected manoeuvres. These differences were used to refine the fuzzy membership functions and rules that govern the assessments of the driving tasks.

Next, this research focused on providing an integrated visual assessment interface to both driver trainers and their trainees. By providing a rich set of interactive graphical interfaces, displaying information about the driving tasks, Intelligent Driver Training System (IDTS) visualisation module has the potential to give empirical feedback to its users. Lastly, the validation of the IDTS system’s assessment was conducted by comparing IDTS objective assessments, for the driving experiment, with the subjective assessments of the driver trainers for particular manoeuvres. Results show that not only IDTS was able to match the subjective assessments made by driver trainers during the driving experiment but
also identified some additional driving manoeuvres performed in low competency that were not identified by the driver trainers due to increased mental workload of trainers when assessing multiple variables that constitute driving. The validation of IDTS emphasized the need for an automated assessment tool that can segment the manoeuvres from the driving scenario, further investigate the variables within that manoeuvre to determine the manoeuvre’s competency and provide integrated visualisation regarding the manoeuvre to its users (i.e. trainers and trainees). Through analysis and validation it was shown that IDTS is a useful assistance tool for driver trainers to empirically assess and potentially provide feedback regarding the manoeuvres undertaken by the drivers.
I have been fortunate to be advised by Assoc/Prof. Andry Rakotonirainy and Dr. Frédéric Maire. They have taught me much about ITS domain and how to conduct research. I am grateful for the time that they have spent discussing ideas, revising papers, commenting on talks, writing grant applications and helping me work on the research that is presented in this thesis. I appreciate the time that the panel members of my thesis committee spent reading this thesis carefully and making suggestions for its improvements. Additionally, many thanks go to the members of the Center of Accident Research and Road Safety – Queensland for their technical and administrative support.

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Acronyms

4WD : Four Wheel Drive
ADAS : Advanced Driver Assistance System
CARRS-Q : Centre for Accident Research and Road Safety Queensland
DVE : Driver Vehicle and Environment
GLM : Generalised Linear Model
HMM : Hidden Markov Model
IDTS : Intelligent Driver Training System
ITS : Intelligent Transportation System
NN : Neural Network
QUT : Queensland University of Technology
XML : Extensible Markup Language
List of Publications


Statement of Authorship

The work contained in this thesis has not been previously submitted to meet requirements for an award at this or any other higher education institution. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the text.

Husnain Malik

Date: / /
Chapter 1

Introduction

Traffic injuries are the ninth leading cause of death worldwide (WHO, 2009). Public health experts say that without intervention, traffic related deaths will rise to fifth leading cause of death within 20 years, surpassing AIDS and tuberculosis (WHO, 2009). It is estimated that 1.2 million persons are killed each year, with up to 50 million injured around the world (WHO, 2009). Road traffic crashes cost an estimated US$518 billion globally in material, health and other expenditure (EMCT, 2006). The burden of crashes is counted not only in lives and permanent injuries but also as a cost to the society. Enhanced road safety is a high priority objective not only for government agencies such as the National Transportation Safety Administration but also for most automobile manufacturers and research centres (TSF, 2003). Driver training is one of the interventions aimed at decreasing the number of crashes involving young drivers. This chapter aims to present the motivation and need to assess driving competencies, using Advanced Driver Assistance Systems (ADAS), in a driver training context.

This chapter is organised as follows, Section 1.1 presents road crash statistics and the significance of dealing with inexperienced drivers to enhance road safety. Section 1.2 presents the research problem in detail. This section will also outline the thesis objective and approach in assessing driving competencies. Significant contributions of this thesis along with the thesis overview are presented in Section 1.3 and 1.4 respectively.
1.1 Rationale

Automobiles have greatly improved the transportation of goods and people around the globe. In return this factor has enabled us to advance in many other areas. Crashes have been the most prominent danger associated with automobiles and often result in serious injuries or loss of human life. Road safety has become a major problem in transportation around the world.

1.1.1 Road Crashes

In 2005, more than 43,000 people died in automobile crashes in the United States, the highest number since 1990. In 2005, on average, 119 people died every day in vehicle crashes, one every 12 minutes (NHTSA, 2005). In Australia during 2006, road crashes cost the Australian community an estimated $18 billion dollars for that year (ATC, 2008) and represent three percent of the Australian Gross Domestic Product (BTE, 2000). The unrecoverable loss occurred in the form of 1627 fatalities (BTE, 2000) however even though these figures are high, the encouraging trend is that road fatalities have decreased compared to the previous years (refer to Figure 1.1) (BTE, 2000). In the 12 months to 30 June 2008, the national road fatality rate stood at 7.2 deaths per 100,000 of population. In-order to achieve the target set by National Road Safety Strategy of 5.6 deaths per 100,000 by the end of 2010, the fatality rate should have been 6.4 instead of 7.2 (ATSB, 2008).

![Figure 1.1: Deaths and Population per 100,000 in Australia](image)
In Australia, road fatalities have been recorded since 1925 and Figure 1.1 shows that fatalities peaked in 1970 and since then, there has been a downward trend even though population has increased. This downward trend in road fatalities can mainly be attributed to the effective road crash countermeasures implemented such as addition of Blood Alcohol level (BAC), seatbelts, random breath tests, improved medical and emergency procedures and technological advancements, which all acted as positive enforcements in reducing fatalities (Zaidel, 2002).

Nevertheless, road safety is still an important issue because of their social costs to the society. Research suggests that even though road fatalities have decreased in the past decade, the social cost of crashes has increased considerably (QT, 2009). Social costs include elements related to hospitalisation, medical treatment, minor injury and property damage.

Table 1.1 shows many factors contributing to crashes which can be related to road (e.g. slippery, potholes), vehicle (e.g. defects) or driver (e.g. inattention, fatigue, illegal manoeuvre). Road crash contributing factors can be categorised as human errors, road conditions and/or vehicular defects. From Table 1.1, it can be observed that road conditions and vehicle defects contribute minimally to crashes compared to human errors. Most crashes are a result of human/driver error and these errors responsible for 90 percent of all crashes (Shinar, 1978). This highlights the need of extra efforts targeting hazardous driving behaviour. In Table 1.1, illegal manoeuvre, inexperience, speed, inattention, fatigue and inattention are categorised as driver error that will be scrutinized in this research (marked grey).

Many factors such as driver’s perception and their learning about a particular driving hazard remain a key factor impacting road safety. Despite this, relatively little is known about the types of errors that drivers make and of the causal factors that contribute to these errors. This is due in part to a lack of structured methods available for collecting human error data within road transport and also, in instances when data does exist, an absence of valid taxonomic systems to accurately classify driver errors and their causal factors (Stanton and Salmon, 2009). Therefore, a multidisciplinary research effort is required to uncover a reliable resolution to road
safety issues including involvement from various research fields such as computer science, automotive engineering, psychology and cognitive science.

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<td>Inexperience</td>
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<td>Inattention</td>
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</tr>
<tr>
<td>Fatigue Related</td>
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<td>5</td>
</tr>
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<td>Age (Lack of Perception)</td>
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</tr>
<tr>
<td>Fail to Give Way or Stop</td>
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<td>Other Driver Conditions</td>
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<td><strong>Total</strong></td>
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<td><strong>820485</strong></td>
</tr>
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</table>

Table 1.1: Contributing factors to road crashes in Queensland between 1992 and 2007

1.1.2 The Inexperience Factor

Even though the advances in technology have improved safety devices and road infrastructure, less effort has been focused on aspects of human factors (Hong et. al., 2005). Research further suggests that road crashes are the single biggest killer of people aged 15-24 years old in industrialised countries (ECMT, 2006). New drivers of all ages have a higher crash risk than more experienced drivers, however, of all new drivers, it is the youngest drivers that have the highest crash risk (Ferguson, Teoh and McCartt, 2007). This is alarming since young drivers (i.e. under 25) consist of only 10% of the whole population but account for approximately 27% of driver fatalities across Organisation for Economic Co-operation and Development (ECMT) countries. Furthermore, between 20% and 30% of total traffic fatalities
result from crashes involving a young driver (ECMT, 2006), and it appears that risks involving young drivers are rising (Twisk and Stacey, 2007).

![Figure 1.2: Driver ages and serious casualty crashes per distance travelled in Australia in 1996 (Fildes et. al. 2001).](image)

Furthermore, the social and economic costs associated with the overrepresentation of these group of drivers makes it a vital aspect for future road safety initiatives (ECMT, 2006). Even though there is a lot of work concerned with safety strategies and training to reduce the rate of young and inexperienced driver crashes, such rates remain unacceptably high. Unless more comprehensive global action is taken, the number of deaths and injuries is likely to rise significantly (Twisk and Stacey, 2007). Therefore, solutions for monitoring, assisting and improving the performance of inexperienced drivers are imperative. Figure 1.2 displays the over involvement of young drivers involved in crashes.

The three main contributing factors toward a young drivers’ involvement in a crash are – lack of experience, age and gender (ECMT, 2006; Twisk and Stacey, 2007). Young men are particularly at risk, with death rates up to three times higher than those for young women (Twisk and Stacey, 2007). Driving is a complex task which requires the driver to assess subjectively their position with respect to the lanes and surrounding vehicles and anticipate the future trajectory of their vehicle within that scenario. Therefore driving safely requires extensive practice and with time, driving actions i.e. changing gears, looking in the rear-view mirror, steering, correctly assessing situations, reacting appropriately, etc. eventually becomes a naturalistic behaviour and more efficient. However, the novice driver has to think about these actions, increasing overall mental workload and possibly getting distracted from the road (Clarke, Foryst and Wright, 2005). It has been demonstrated that a major
contribute factor to crashes of newly licensed driver, is the failure to scan effectively for potential risks (McKnight et. al. 2003, Treat et.al. 1979, Fisher and Pollatsek 2008, Pradhan et.al. 2005).

1.1.3 Driver Training Implications for Road Safety

The value and effectiveness of driver training as a mean of improving driver behaviour and road safety continues to fuel research and societal debates. Knowledge about what are the subjective and objective characteristics of safe and unsafe driving is extensive (Hong, Chung and Kim, 2005, Ferguson et. al. 2007 and ECMT 2006). Generally, young drivers’ high involvement in road crashes is often attributed to lack of driving skills. This high crash risk has led to calls for more and better training of novice drivers. Some research literature suggests that changes in traditional pre-license training programs could influence basic car control and road law knowledge skill but will not have significant impact on reducing crashes or traffic violations (Hong et. al., 2005). However, a greater amounts of supervised driving experience during the learner phase has shown to result in reduced post-licence crash involvement in Sweden (around 35%) (Christie, 2001).

Formal training, involving a qualified trainer, has not been proven effective in reducing post licence crash risk despite being mandatory in many systems (Mayhew and Simpson, 2002). However, this does not mean that it has no valuable contribution. Traditional training methods focus primarily on creating drivers who are technically competent and able to pass the driving test. In order to create safe drivers, training should focus on self assessment and teaching an understanding of the factors that contribute to risk (Langford, 2006). Therefore driver training’s impact on road safety cannot be completely ruled out.

Furthermore, parents also have an important role in increasing the amount of supervised driving the novice drivers undertake, which seems to reduce subsequent risky behaviour. One of the key aspects of driver training programs is assessment or feedback on the driving performance. This can either be through self-assessment or assessment from another group or individual. Extensive research has revealed that it is not so much the lack of basic driving skills that is the main cause of crashes involving novice drivers’ but higher order skills. These higher order skills deal with
risk perception, situational awareness, risk acceptance and self-assessment (Jose and Mayora, 2008). Thus, the goal of training should be to create safer drivers, which involve instilling young drivers with a sense of their own limitations and understanding of the risks and its causes.

1.2 Research Problem

Novice drivers are at greatest crash risk in the first six months of solo driving (Williams and Ferguson, 2004). Driver training is one of the interventions aimed at mitigating the number of crashes that involve young drivers. Our failure to understand what is really important for learners, in terms of high level of competent driving, is one of the many reasons constraining the building of better training programs. It is not possible for trainers and driving mentors to simultaneously assess drivers’ actions accurately, cognitive skill and vehicle control, relative to environmental circumstances. However, Advanced Driving Assistance Systems (ADAS) acting as in-vehicle devices can add a significant set of useful functionalities to existing driver training programs. Such new functionalities offer possibilities to enrich and improve the learner’s understanding of the driving task. Along with this, during driving events such as lane changes and lead vehicle braking events, drivers are sometimes too close to lead-vehicles for a proportion of a trip, even if they are driving safely. This raises the question ‘What separates the safe from unsafe following?’ Similarly, for most of the critical driving skills, empirical answers are needed to design a customised driver feedback technology that can post process driving tasks and evaluate manoeuvres to increase traffic safety.

1.2.1 Thesis Objective

The aim of this research is to design, develop and evaluate an in-vehicle assessment tool that assists trainers to objectively assess driving competencies by:

- Designing a driving experiment that can identify differences in novice and experienced drivers;
- Defining a driving competency model that trainers will use to empirically assess the safety of driving manoeuvres;
• Designing an integrated visual interface regarding the driving tasks that assists driver trainers in effectively communicating high / low competency of manoeuvres performed by drivers.

Currently, there is no automated system that can integrate parameters concerning vehicle dynamics, driver behaviour and environmental information in-order to assess drivers’ manoeuvres. The current research addresses this gap by initially acquiring information for the above mentioned parameters through cameras and multipurpose sensors. This data is then integrated and analysed in order to assess driving performance. An integrated visualisation mechanism, utilizing fuzzy set theory is designed to present evaluations and a holistic view for each manoeuvre executed during the driving scenario.

1.2.2 Research Statement

This research extends the current knowledge on differences in experienced and novice driver performance. Inexperience is widely acknowledged as one of the most persistent safety problems for all motor vehicle users. Report suggests that 31.7% of the circumstances contributing to the crashes of young people can be attributed to inexperience (QT, 2002). Driver training has been identified as one of the countermeasures used to reduce this crash risk involving young drivers; however there is no consensus on the teaching requirements. Most of the programs are based on commonsense rather than scientific knowledge (Henderson, 1991). Researchers believe that even though some of these programs are thoughtfully and carefully planned, they have not been evaluated (Williams and Ferguson, 2004). Currently, there is a need to develop and evaluate automated Advanced Driver Assistance Systems (ADAS) that could assess driving competencies. The aim of this research is to develop an autonomous system called Intelligent Driver Training System (IDTS) that analyses competency level of the driver in a given driving situation. This multidisciplinary research project will develop and validate a unique driver assessment tool which will assist both drivers and driver trainers/parents to assess young drivers’ driving competencies by post processing the driving tasks, and providing a rich visual interface for potential feedback.
To our knowledge, no such automated system exists that can comprehensively evaluate and assess a given driving situation. In order to develop useful measures to tackle road safety issues, a complete and integrated framework needs to be developed that will include and examine all the parameters that influence driving (i.e. cues related to road, vehicle and driver). Since driver trainers are competent drivers, we hypothesize that their driving can be modelled as highly competent which can later be used to assess driver trainee’s competencies. Drivers that do not satisfy the high competency driving model will be assessed as less competent. Such a system will assess the level of competency (low, medium, and high) for the driving manoeuvres, based on the parameters acquired from the Driver, Vehicle and Environment (DVE). Once the assessment has been made, a visual representation of the driving tasks (i.e. for potential feedback) needs to be put in place that can help driver trainers explain the driving errors of novice trainee drivers more accurately.

The main research questions addressed are:

- What differences exist between novice and experienced drivers when they perform certain driving manoeuvres?
- Can these differences be objectively evaluated using expert knowledge (by fuzzy rules) and assessed between high or low competence levels?
- Can an interactive visual interface that presents the driving task’s assessments and potential feedback be developed in an effective manner?

As mentioned previously, a framework that has the ability to identify and assess driving differences in novice and experience drivers is needed. Potential benefits of such a framework include identifying and refining driving abilities that are required for skilled driving. Additionally, the potential feedback mechanism of such a framework has the ability to identify the manoeuvre performed in a low competent manner to its users (i.e. trainers or drivers) and potentially improve it.

1.2.3 Approach

The main purpose of this research is to provide a better understanding of the driving performance amongst novice and experienced drivers. Driving in a dynamic
environment can be a complex task as it requires drivers to visually track objects, constantly monitor changing driving situations and road conditions and make decisions under potentially high workload. Highly competent driving constitutes in-time accurate observation, anticipation and reaction. A lack on the driver’s part in any of the three tasks (i.e. observation, anticipation and reaction) can lead to a potentially high risk situation. In order to comprehensively evaluate the driving scenario, multiple variables are gathered and recorded. These variables are related to Driver, Vehicle and Environment (DVE) and are recorded through cameras, laser scanners and multipurpose sensors. Some of these variables include following distance, frequency of mirror checks, gaze depth and scan area, distance with respect to lanes and excessive acceleration or braking. These variables are recorded for a set of manoeuvres that constitute a driving task such as turns, overtake, t-crossing and lane change.

Research has shown that there are differences in risk perception between novice and experienced drivers (Ivers et. al, 2009). These differences should result in creating a distinction in on-road driving while both groups (i.e. novice and experienced) perform similar manoeuvres. To address these differences in driving, a driving experiment was conducted on a closed loop track with both groups of drivers performing the selected manoeuvres under the supervision of driver trainers and the recording system of the driving tasks. Driver trainers (i.e. expert knowledge) were required to subjectively evaluate the driving skills of the driver, while the recording system for the driving tasks, segmented out the selected manoeuvres and the variables recorded during the driving. This driving experiment helped identify the driving differences in novice and experienced drivers while performing the selected manoeuvres.

Secondly, once the differences between the groups were identified, a competency assessment scale was defined. This assessment scale was devised based on the differences identified from the driving experiment. Driver trainers (i.e. expert knowledge) were consulted to confirm the devised scale. The driver’s decision and response on processing the stimulus is not accurate but rather an estimate. Furthermore, the driver trainers’ assessment is uncertain as well, given their subjective perception. By exploiting fuzzy set theory, which allows dealing with
uncertainties, a high and low competency driving model was designed. Fuzzy set theory helped to effectively model low/high competency driving by observing both novice and experienced drivers.

Finally, a visualisation module was designed to present driver undertaking of the driving tasks. This module contains visualisation of the driving tasks and their associated competency scale which is an integral part of this project. Since its end users are driver trainers, it is necessary that all driving data and less competently performed manoeuvres are represented in a way that is easy to comprehend. Hence, it will be easy for the driver trainers to explain some specific situation to the driver.

1.3 Thesis Contributions

The research presented in this PhD thesis is multidisciplinary and contributes to the knowledge of many different fields. The contributions to the different disciplines are given below:

1.3.1 Road Safety

Innovation:
This research objectively identifies the driving performance differences amongst the recorded variables for novice and experienced drivers. It further highlights the relationship between the differences (i.e. how change in one variable affects other variables). Currently, driver training is based on subjective evaluation of the driver trainer. This research will provide methodology to objectively evaluate drivers’ performance.

Significance:
Almost one-third of drivers killed in motor vehicle crashes on Australian roads were aged between 17 and 25 years. Implementation of intelligent driver education systems that can reduce this burden is a social and economic imperative. This research is designed to enhance driver training, with the aim of reducing the over-representation of young and inexperienced drivers in road crashes.

1.3.2 Computer Science

Innovation:
The first contribution of this thesis to the field of computer science, is the evaluation of the driving manoeuvres and the tasks involved in performing these manoeuvres using fuzzy logic. The second contribution is the estimation of drivers’ gaze depth (in metres) using a perspective projection algorithm that exploits the road parameters (i.e. actual distance between lane markings (in metres), distance between lane markings on the image of the road acquired (in pixels) and horizon point on the image of the road). The final contribution is the automated segmentation of the selected driving manoeuvres (i.e. turn, overtake and lane change) from the complete driving scenario. Along with the segmentation of manoeuvres, each manoeuvre is further sub-divided into three parts namely: pre-manoeuvre, manoeuvre and post-manoeuvre. This helps to objectively assess the driver performance not just during the manoeuvre but even at the approach and end of a particular manoeuvre.

**Significance:**
This research provides a method in monitoring multiple variables related to DVE and evaluate, utilising fuzzy logic, multiple driving manoeuvres in an automated manner. The gaze depth plays a significant role during driving, since driver trainers and researchers mention that looking lower on the road in front leads to lower reaction time if a hazard occurs along with jerky steering movements. Hence evaluation of gaze depth can contribute to better understanding of drivers’ behaviour.

### 1.3.3 Driver Performance Assessment Modelling

**Innovation:**
Competency assessment of all selected driving manoeuvres is presented in this thesis. The research demonstrates the use of fuzzy set theory for performance assessment modelling. Other mathematical models to assess performance are also introduced. Based on these competency assessments, driver trainers will be able to more effectively evaluate strengths and weaknesses of drivers.

**Significance:**
The assessment model, based on fuzzy logic highlighted in this thesis is flexible in accommodating uncertainties in driving behaviour. It is also adaptable to change and addition of new assessments required for monitoring driver performance.
1.3.4 Visual Feedback in Driver Training

**Innovation:**
This research presents a rich graphical user interface that can potentially be used to provide feedback to both drivers and their trainers. This interactive interface features a map visualising vehicle trajectory and recorded data for the driving tasks. The competency assessments for the selected manoeuvres are also overlayed on the map. An integrated graphical mapping of the data collected during the driving scenario allows the collected and processed data to be actionable intelligence, rather than just organised information.

**Significance:**
By using the visualisation interface regarding the driving tasks, driver trainers can potentially provide integrated feedback to their trainees. The trainees can also benefit from this interface by having a holistic view of their execution of driving manoeuvres. Furthermore, driver trainers can objectively/empirically assess the driving parameters, which they currently are unable to perform due to the subjective nature of assessments.

1.4 Thesis Outline

This thesis is comprised of eight chapters including introduction. The first chapter has provided the rationale and objectives for this research work. An extensive review of driver training programs is presented in Chapter 2. This chapter presents the novice driver problem in a driver training context. It further discusses the driver, vehicle and environment (DVE) model in the light of hazard and risk perception. It also presents the human machine interface model and the modification of this model to incorporate environment for driving related tasks. Chapter 3 presents a review of various Intelligent Transportations System (ITS) used to monitor different aspects of driving. It also presents the integration of multisensory data and processing of that data in the context of driver training. A review of different performance assessment methodologies is presented in Chapter 4. This chapter discusses the use of fuzzy set theory in handling uncertainty involved while assessing driving manoeuvres.

A detailed description of the framework and its prototype for automated training system called Intelligent Driver Training System (IDTS) is presented in Chapters 5,
6 and 7. Chapter 5 presents the component design and prototype of IDTS. Chapter 6 describes the driving performance protocol necessary to evaluate performance of the driving manoeuvres. It presents details regarding the driving experiment conducted to identify differences between novice and experienced drivers. This chapter focuses on the variety of identified recorded variables that vary with experience. It also discusses the analysis of the driving tasks and correlation between the variables recorded (from DVE) during the driving experiment. Chapter 7 focuses on an integrated visualisation module of IDTS. This chapter also validates the findings and objective evaluations of IDTS with that of a driver trainers’ subjective assessment. Chapter 8 concludes the thesis with a summary of the work presented in previous chapters. It also discusses the outcomes and limitations of this research. Lastly, the guidelines for future research in driving manoeuvre evaluation are presented.

Figure 1.3: Pictorial representation of the chapters in this thesis
The Role of Driver Education

Safety analysis of road situations is not limited to the detection of information about existing crash risks such as obstacles but requires skills to predict the position of the obstacle in the future. Driving situations (i.e. driving tasks, environment) are complex and vary constantly, resulting in drivers having to perform continuous decision making based on those variable stimuli conditions. Correct receiving and processing of perceived information enables the driver to make cognitive decisions and manoeuvre according to each traffic situation. Endsley (1995, p. 36) refers to this as a situation awareness which is defined as “perception of environmental elements in terms of time and spatial measurements understanding their meaning and foreseeing their state in the immediate future”. The viewing of the road and accurate perception of environmental elements is necessary in avoiding crashes because vehicle dynamics limits the car in making sudden speed or directional changes. Safety analysis of traffic situations involving driver, vehicle, environment and their interaction is a difficult task for perception, modelling, decision and control. Learner drivers at the pre-licence level have long been the target of various types of driver training efforts ranging from simple one-to-one instruction to elaborate mandatory schemes within driver licensing programs (Saffron, 1981). The aim of this chapter is to present the novice driver problem in the context of driver education.
This chapter is organised as follows: Section 2.1 presents the role of driver education and training in the light of fundamental approaches used for injury prevention. It discusses the novice driver problem and limitations in the current training programs. It also further describes the use of Intelligent Transportation System (ITS) to improve driver training. The problems involving novice driver education and limitations of the current driver training programs are presented in sections 2.2 and 2.3 respectively. Section 2.4 elaborates on the complexity of driving tasks and role of hazard and risk perception in highly competent driving. Section 2.5 introduces the benefits of using visualization techniques for potentially efficient feedback regarding the driving tasks. Section 2.6 presents the summary of the entire chapter.

2.1 Engineering, Enforcement, Education and Engagement

The three fundamental approaches for road injury prevention are engineering, enforcement and education (Hedlund, 2000 and NRCIM, 1985). Engagement or encouragement was later added as another approach for prevention (LATMP, 2005).

- **Engineering** or technology approaches - are ones that provide automatic solutions using engineering interventions. This process includes identifying and developing solution for known road safety issues and reviewing the effectiveness of road safety measures. Examples of direct technology solutions for improving road safety include crash prevention technologies (active safety) such as driver warning system and crash worthy technologies (passive safety) such as Antilock Braking System (ABS) and air bags (Hedlund, 2000) while road engineering solutions includes sign boards, sidewalks and road design.

- **Enforcement** - are regulations designed to change road user behaviour so as to bring about increased safety. An example of enforcement is mandatory seat belt law, which together with the system of fines and penalties discourage unsafe driver behaviour (i.e. not using seat belt) and encourages safe driver behaviour (Hedlund, 2000).

- **Education** or social solutions – are procedures designed to persuade the public (road users in this case) to change their behaviour voluntarily. These include
strategies in influencing people to adhere to a certain behaviour or policy. Unlike enforcement which forces mandatory change, education provides an indirect method of persuasion (e.g. public awareness through media) to change certain behaviours. Incentives are known to act as encouragements since public will want to benefit from the incentive (Hedlund, 2000).

- **Engagement** - or Encouragement is another key component of the prevention programs. From a road safety point of view, convincing road users about safe road use and motivating them to help solve the ongoing issues is part of the engagement process. Encouragement activities can often be easy as well as inexpensive to start. Engagement is a generic term to describe a broad range of interactions amongst people. For example walk to work day, consultation sessions with a particular group of road users.

Indeed, engineering, enforcement, education and engagement are fundamental for road injury prevention. Ensuring safety by using only engineering or technology solutions is the most effective whereas guaranteeing safety using moral persuasion is the least effective (Hedlund, 2000). The main reason is that with some technology protection such as air bags and anti lock braking systems, very little driver participation is required. Whereas with education, dependence on drivers to change their behaviour is high, thus hindering the approach to be effective (Hedlund, 2000). The most effective approach is to combine all the above mentioned aspects (i.e. engineering, enforcement, education and engagement) in a coordinated manner. Researchers in (UDTFHA, 2004) presented a solution to a road safety problem (red light running - RLR). RLR cameras were proposed to reduce RLR violations thus reducing RLR crashes. In order to effectively handle these problems using the four E’s approach, the following tasks were practiced (UDTFHA, 2004).

- Conduct an engineering study before considering camera installation.
- Evaluate effective engineering and education alternatives before considering photo enforcement.
- Ensure the red-light camera program is engineered and installed properly.
- Measure, document and make safety results available.
- Ensure complete oversight and supervision by public agencies.
• Include an ongoing photo-enforcement public education program and engage the community.

By using the RLR cameras, the number of crashes at signalised intersections reduced by 7 percent and the number of injury crashes reduced by 29 percent (UDTFHA, 2004).

### 2.2 The Novice Driver Problem

Throughout the world, drivers are killed or injured in road traffic crashes with young drivers at greater risk, and this problem remains largely unsolved (Harre, Brandt and Dawe, 2000). Research suggests drivers aged 15–24 years are at the highest risk (approximately three times more than 45-49 year olds) of motor vehicle traffic crashes (Harre, Brandt and Dawe, 2000). During the first years after having passed the driving test, the crash risk declines sharply. Several studies have found that the crash risk decreases rapidly after the first years of driving experience (Turetschek, 2006). However, it takes about 7 years of driving experience before the crash risk reaches an acceptable, low level (Turetschek, 2006). Better understanding of the underlying factors that lead to young drivers’ crashes is a necessary step in preventing crashes and fatalities. To change a young driver’s goals behind driving and the context in which it is done, a variety of different methods of persuasion should be tested. Young drivers demonstrate risky attitudes and dangerous driving practices such as speeding and not wearing a seat belt (Harre et. al., 2000). These risky attitudes may be the result of a general overconfidence that young people have with regard to their driving abilities (Deery, 1999) and an overestimation of their ability to recover from error should one occur (Brown, 1982). Not all young people, however, engage in risky driving behaviour. Therefore, it is necessary to develop interventions that will effectively target the risky group.

Gaining sufficient road experience is an important factor that minimises crash risk. However the age at which young people are allowed to start solo driving is equally important. Research suggests that lower the minimum driving age is, the higher the crash rate amongst novice drivers (ECMT, 2006). This leads to a paradox: young drivers need to gain experience to make them safer drivers, but it is this process of solo driving that exposes them to crash risks. Young people are physically and emotionally less mature, and thus less able to assess risk than older drivers. Recent
research indicated that the parts of the brain responsible for inhibiting impulses and weighing the consequences of decisions may be under development until well after the teenage years. Young drivers are often testing boundaries and asserting their independence, as well as typically having an intense social life (ECMT, 2006). This includes being active at night and on weekends, often carrying passengers of a similar age group. They may be inclined to show off, be vulnerable to peer pressure and drive too fast or under the influence of alcohol or drugs.

It is often said that safe drivers are made, not born (Deery, 1999). Therefore, young drivers need to obtain substantial experience in lower-risk conditions before being allowed on the roads. Research suggests that high levels of accompanied driving practice in a variety of driving situation will result in lower levels of fatalities (Deery, 1999).

There is little reason to think that driver training could produce drivers that are less likely to be involved in crashes since the training courses are of short durations (Williams and Ferguson, 2004). There is less opportunity to teach safe driving techniques in a short timeframe and any safety messages that are conveyed can be overwhelmed by ongoing parental, peer, personal, and other social influences that shape driving styles and crash involvement. Such influences largely are beyond the reach of driver education instructors (Williams and Ferguson, 2004). Still, the benefits of driver training cannot be completely rejected. It seems apparent that driver training should be considered as one of the many methods for teaching young people how to drive safely but one of the issues is that there is no standardised method for educating young drivers in Australia. However, it is expected that professional driver trainers will be able to effectively provide instructions for teaching and evaluating young drivers. Nonetheless, even professional driver trainers’ assessment is subjective rather than objective. Objective assessments can be provided using engineering and technology solutions.

Research suggests that long term solutions to train drivers are technological solutions (Deery, 1999). These technological solutions can be used for monitoring, enforcement, and for assisting the novice driver with the driving task. While the potential is high, the actual gains to be achieved from new technologies are
unknown and there will initially be costs for implementing technology in vehicles. This implementation of technological solutions could result in resistance from drivers and vehicle manufacturers.

2.2.1 Goal for Driver Education

There is continuing debate about the worthiness of driver training as means of improving driver performance to reduce crashes. It has been argued that driver training and driver education are not the same, the former is a subset of the latter (Christie, 1996; Horneman, 1993 and Watson et. al, 1996). However, it has become common even in the scientific literature for these terms to be used interchangeably.

Horneman (1993) mentioned that driver training and driver education can be differentiated as:

- Driver training relates to car control or to the techniques of handling a vehicle.
- Driver education is a broader term which may include driver training but extends to a fuller knowledge and understanding of the driving task in all its complexity.

West Virginia Board of Education Policy (Paine, 2008, p.4) defines goal of driver education as: “The goals of the Driver Education Program of Study are to provide students with the knowledge and skills to safely and efficiently operate a motor vehicle on our nation’s streets and highways, to equip students with the knowledge to enable them to make wise decisions as drivers, and to assist students to become responsible users of the highway transportation system.”

The head of the Royal Society for Prevention of Accident (Education, 2008), while talking about driver education argued that, “This is not about how you control the vehicle, but how you behave out on the road, look and anticipate and how your behaviour affects others, so education is crucial”. Many driver education curricula, public and private, have been developed without the benefit of information as to what constitutes an effective program (NTSB, 2003).
In order to strengthen driver training programs, Christie (2001) suggests some additions to conventional training programs for young drivers. They are:

- Encourage the acquisition of more experience under a greater range of driving conditions, especially during the learner period when the learner is accompanied by an experienced driver and has a reduced crash risk (Gregersen, Nyberg and Berg, 2003).
- Use graduated licensing principles to ensure that the learning driver is exposed to the full range of driving conditions in a systematic and controlled manner.
- Improved assessment of higher-order driving skills within licensing structures, in particular, hazard perception skills. Continue to develop and evaluate new approaches to training that transcend the conventional focus upon basic driving skills and road knowledge.

Graduated Driver Licensing (GDL) is one of the recent developments in driver licensing and gradually introduces new drivers to more complex driving situations as they progressively gain driving experience (Watson, 2003). GDL is designed to reduce young driver’s exposure to risky behaviours by requiring the new driver to progress through stages until full licensing is achieved, while still permitting drivers access to gain real experience on the road. Research has shown that GDL is intended to reduce the inexperienced driver’s crash risk by limiting their exposure to dangerous situations on the road (Watson, 2003). The learner licence phase provides an opportunity for learner drivers to practice the necessary skills under the supervision of a more experienced driver, such as a parent or instructor. Upon graduating from the learner stage, the provisional licence phase allows for solo driving, however, this is subject to certain restrictions such as passenger restrictions and late night driving. Many GDL programs include the application of additional restrictions to the inexperienced driver, such as zero blood alcohol concentration (BAC) and a limit on the accumulation of demerit points (Williams and Mayhew, 2003). Once the provisional driver graduates to an open licence they have full driving privileges.

There is a strong link between the introduction of more stringent graduated driver licensing schemes, including the restrictions discussed previously, and crash reductions (Bates, Watson and King, 2006). In contrast to the lack of evidence for
driver training, evaluations of GDL systems around the world have demonstrated reductions in crashes ranging from 4% to 60% (Simpson, 2003). This large difference is in part attributed to great variations in the GDL components included in each jurisdiction (e.g. night driving, no high powered vehicles), the different ages that apply to various stages, and the different methodologies employed (Simpson, 2003). While driver training and graduated driver licensing have historically been treated as separate or competing countermeasures, there is preliminary evidence from evaluation studies in the USA supporting the integration of these two approaches (Zhao, 2006).

In this regard, driving instructors and parents have a key role in working collaboratively with inexperienced drivers for both experiential and instructed learning. Driving restrictions imposed by parents on initial driving privileges can also reduce exposure to high risk driving conditions, thus reducing crash risk while learner's driving proficiency is developed. Both instructors and parents have an opportunity to establish and nurture drivers' productive patterns of thinking and to promote higher levels of awareness around their own learning and driving ability. However this requires a better system for logging and diagnosing performance during training together with a framework enabling parents-instructors-learners to discuss the learner's performance. Such a framework should be systematically integrated across the whole GDL learning phase. This research will aid in objective assessment of the Graduated Driver Licensing (GDL) program by addressing the research questions related to:

- Dealing with the aspect of driving for less experienced drivers.
- Logging and diagnosing driving behaviour during training.
- Providing a framework enabling instructors and learners to discuss the learner's performance.

Another aspect of the GDL framework consists of three goals for training: knowledge and skill, risk-increasing factors, and skills for self-assessment (Mayora, 2008). These dimensions relate to behaviour at the different levels thus influencing driving preconditions as well as the accomplishment and execution of the driving task. First, the knowledge and skill level refers to the skills a driver needs for driving under different circumstances. Secondly, risk-increasing factors deal with aspects of driving or traffic that may increase the risk such as perception of the traffic
situation, speed adjustment, and risk acceptance. Lastly, the skills for self-assessment refer to the driver's capability to assess their performance. It relates to critical self-adjustments of all dimensions starting from skills in vehicle handling to a reflection of individual risk attitudes (Mayora, 2008).

Graduated licensing systems do not attempt to train drivers, or to educate them as to how they should drive. They merely encourage novices to drive at times and in situations known to entail lesser risk, so that they gain essential practical experience as safely as possible (Foss, 2009). The most appropriate goal for formal driver education is to be the most effective way to teach basic driving skills and generally educate students about driving. It is clear however, that neither the ability to handle a vehicle nor the knowledge of road rules, equate to driving safety. Although the development of skills is largely dependent on experience, the actual driving behaviour of young novices is shaped by many other factors including personal dispositions, motivations, lifestyle, decision making abilities, neurocognitive development, the influence of parents and peers, along with the behaviour of other drivers on the road (Deery, 1999).

**GADGET Matrix** introduces that the traditional driver training is mostly limited to focusing on basic skills and knowledge on vehicle manoeuvring and mastery of traffic situations, with some attention is given to risk increasing factors (Hatakka et. al., 2003). A description of the different levels of driving behaviour was developed as part of the EU project (GADGET matrix (Siegrist et. al., 1999)). The matrix is based on the assumption that the driving task can be described as a hierarchy. The idea of the hierarchical approach is that abilities and preconditions on a higher level influence the demands, decisions and behaviour on a lower level.

The following four levels are described by Keskinen and were also later applied in the EU-project GADGET (Hatakka et. al., 2003).

- Goals for life and skills for living (4th level)
- Goals and context of driving (3rd level)
- Driving in traffic situations (2nd level)
- Vehicle control (1st level)
CHAPTER 2. DRIVER EDUCATION

The fourth and highest level refers to personal motives and tendencies in a broader perspective. This level is based on knowledge that lifestyles, social background, gender, age and other individual preconditions have an influence on attitudes, driving behaviour and crash involvement (Hatakka et. al., 2003). On the third level, the focus is on the goals behind driving and the context in which driving is performed. For example, it includes choice between car and bus, daytime or night time, decision to drive under the influence of alcohol, fatigue and stress, all in relation to the purpose of the trip. The second level is about mastering driving in traffic situations which are defined as more limited than the driving context above. A driver must be able to adapt their driving in accordance with the constant changes in traffic, for example in junctions, when overtaking or when encountering vulnerable road users. The ability to identify potential hazards in traffic is also applicable to this level.

The bottom level emphasises the vehicle, its construction and how it is manoeuvred. Knowing how to start, change gears, etc. well enough to be able to use the car in traffic belongs to this level as well as more complex evasive manoeuvres, reducing skids on low friction and understanding the laws of physical forces. The functions and benefits of injury preventive systems such as seat belts and airbags also belong to the bottom level. Driver training traditionally focuses on levels 1 and 2 (Hatakka et. al., 2003). All four levels are presented in table 2.1 below.
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Table 2.1: EU Project Gadget Matrix (Driver behaviour model) (After Hatakka et. al., 2003)

A safe driver is, however, not only skilled but also aware of risks and of his own abilities/competencies and characteristics as a person. In order to cover these different dimensions the hierarchy was expanded into a matrix which - in addition to the four levels – includes the following three dimensions (Hatakka et. al., 2003):

- Knowledge and skills
- Risk increasing factors
- Self evaluation

The content of the first column describes the knowledge and skills that a driver needs for driving under normal circumstances. On the lower hierarchical levels, this equates to how to manoeuvre a car, how to drive in traffic and what rules must be followed. On the higher levels, the column relates to how trips should be planned and how personal characteristics may influence behaviour and safety (Hatakka et. al., 2003).

In the second column about risk-increasing factors, the focus is on awareness of aspects related to traffic and life in general that can be associated with higher risk. On the basic level, this may be worn out tyres, poor brakes, lack of routine in performing basic manoeuvring, etc. Higher in the hierarchy the column refers to risky driving in darkness, on low friction, among vulnerable road users, excessive...
speeding, mental overload, etc. It also relates to dangerous motives and risk-increasing aspects of lifestyle and personality. The third column is about how the driver assesses their own situation on the four levels. It relates to the calibration of one’s skills on the basic levels and awareness of one’s personal characteristics and tendencies, as well as the ability to make decisions about trips and in life in general on the higher levels.

Thus, the cells in the matrix define a framework for the definition of detailed competencies needed to be a safe driver. The matrix can be used for defining educational goals and educational content in driver training. A holistic driver training should strive to cover the whole matrix as much as possible and not only the bottom left cells that are traditionally focused on during driver education.

Driver education is constantly reinventing itself and several new programs have been developed recently in the United States, Europe, Australia and New Zealand. These programs are thoughtfully and carefully planned but they have not been evaluated (Williams and Ferguson, 2004). Given the fact that results were disappointing for evaluations of prior driver training programs, it is essential to scientifically evaluate new programs before they are fully launched.

\section*{2.2.2 Self Assessment and Feedback}

The crash risk of young novice drivers is affected by a number of factors which include social and situational influences, driving exposure-related influences and the characteristics of young drivers (Williamson, 1999). Extensive research has revealed that it is not so much the lack of basic driving skills that cause crashes, but higher order skills. These higher order skills deal with risk perception, situational awareness, risk acceptance, self-assessment, and motivation to drive safely (Jose and Mayora, 2008). Williamson presents four categories of young driver factors that are relevant for explaining their heightened crash risk. They are core attributes, modifiable attributes, situation assessment and decision making characteristics as well as the types of behaviour the young driver engages in (Williamson, 1999).

The probability that a driver successfully avoids a hazard increases as the driver is provided more time and distance in which to identify the hazard and execute the
most effective response. Young drivers assess their driving abilities to be better as compared to older drivers (Tronsmoen, 2008). This over confidence on the part of young drivers is a factor affecting novice drivers’ crash risk. Novice drivers need to gain greater self assessment skills and understanding of the factors behind each risk. Persuasive communication should accompany other countermeasures, with a view to changing attitudes and creating greater understanding of risk, noting that attitudes regarding safety are formed years before the driving age, and are highly influenced by the behaviour of role models (ECMT, 2006).

Report (AAMI, 2009) suggests that young drivers’ skills are limited as compared to experienced drivers which they need to realise themselves. Therefore, driver training should make participants undergo a series of practical exercises which allows them to recalibrate their own self-assessment. For example, young drivers should experience how a little extra speed can affect their ability to control their car and discover their reaction to sudden changes in traffic conditions. They also experience what can happen if they have to stop suddenly and discover how much space is actually needed to stop their vehicle. Providing this feedback increases the opportunity for young drivers to experience the limitations of their driving abilities in a controlled and safe environment. Effective feedback and making the young drivers aware of their limitations can address the issue of overconfidence and overestimation (AAMI, 2009).

Authorities could also improve driver training and testing. As mentioned earlier that in GDL framework one of the goals is to create the skills of self-assessment for the drivers. The goal of these processes should be to create safer drivers, which involves instilling novices with a sense of their own limitations and understanding of the causes of risk. New technologies, such as black boxes that record details of how a car is being operated, may help as well however; further research will be required to assess the effectiveness of new technologies that might benefit young and novice drivers.

2.3 Limitations of Skill Based Driver Training

A number of hurdles currently exist in improving road safety for young and inexperienced drivers. For instance experience, age and gender have been identified
as key factors underpinning the high levels of young driver crash risk (ECMT, 2006). It has also been estimated that 31.7% of the circumstances contributing to the crashes of young drivers can be attributed to inexperience (QT, 2005).

When inexperience is identified as a crash risk factor, more intensive and specialised driver training is often perceived by governments and communities to be an effective road safety countermeasure (Watson, 2003). Most driver training programs are oriented towards developing vehicle-handling, road rule knowledge and obtaining the initial drivers’ licence. Researchers worldwide maintain that there is little evidence for pre-licence training to reduce the crash rate amongst inexperienced drivers (Watson, 2003; Bates et. al. 2006; Christie, 2001). Furthermore, the research undertaken to evaluate the safety benefit of driver training is inconclusive.

For instance, researchers (Lynam and Twisk, 1995) found that the post-licence crash rates of those trained by a professional instructor and those trained by a parent or relative were similar. Additionally, the result of studies reviewing the issue of increased skill-based training has generally found an increase in the associated crash risk. In particular, Gregersen (1996) demonstrated the connection between the training strategies and skills. He compared two types of training and their influence on estimated and actual driving skill, as well as the driver’s degree of overestimation of their own skill. One type of training was concentrated on skill training and another one on making the driver aware of his/her limited skills in critical situations. The skill-trained group estimated their skills higher than the insight trained group, even though no difference was found in their actual skills. It was concluded that the skill based strategy produced an overconfidence of ones own skills. Therefore it appears that traditional driver education courses have generally focussed on developing driving skill rather than the wide range of factors influencing inexperienced driver crash risk.

Research conducted in Sweden has shown that increased levels of supervised experience during the pre-licence phase have been associated with reduced post-licence crash involvement of up to 35% (Gregersen, 1996). Findings such as this have prompted many countries (UK, North America, Australia and New Zealand)
to introduce specific amounts of supervised training for inexperienced drivers (Bailey, 2003).

Formal training is not generally proven to be effective in reducing post licence crash risk, despite being mandatory in many systems however, this does not mean that it has no value. But traditional training methods focus primarily on creating drivers who are technically competent and able to pass the driving test. In order to create safe drivers, training should focus on self assessment and on teaching an understanding of the factors that contribute to risk (Deery, 1999).

### 2.3.1 Lack of driver training standards

In addition to the skills taught during driver training, there appears to be a lack of standardisation across the training and education of drivers. Current EU legislation focuses the driving tests on the theory and practical skills required to drive and there is no European-level legislation standardising driver training practices (MERIT, 2005). Of most concern to transport authorities is that at the time their licence is issued many drivers have not gained sufficient experience. In the UK (Groeger and Clegg, 1993), researchers reviewed the European Commission’s DRIVE project to analyse the complete records of 20 people learning to drive and the instruction they received. On average about 2,000 manoeuvres were carried out under instruction before a driver was considered ready to take their driving test of which only 17 participants reflected 92% of all manoeuvres. The implication is that most manoeuvres probably receive far too little practice for standards to be consistent prior to taking the test. Researchers (Groeger and Clegg, 1993) argue that the driver’s level of performance is likely to be quite unstable after the 30 or so hours of training so that the ability to pass the test cannot be predicted because their experience of the different manoeuvres has been fairly random during the training period. This study showed that the distribution of experience in the performance of these manoeuvres is random, depending upon the events encountered, the roads used and the methods of the driving instructor. The use of closed course assessments may not be any better, as it does not generalise to real road conditions and the driver assessment given is reasonably subjective (Galski et al., 1990).
In terms of the performance of the driving instructor, approximately 70% of the manoeuvres were commented upon and some manoeuvres were more likely to attract comments compared to others. Most of the instructions were concerned with car control and less than 10% on reasons why these actions should be performed. Given that most instructions were received when the driver is simply driving ahead, and these comments are generally about car control, most learner drivers have little understanding of where the risk is most likely to occur and this is one factor that contributes to their over representation in post-test crashes. The study shows that instructors appear to concentrate their instruction on factors that do not prepare the driver for solo driving. Consequently, many learner drivers often receive insufficient practice to reach a high and stable level of performance by the time they gain their driving licence. Authorities setting the standards are increasingly concerned that many candidates seem to be able to pass the driving test through good fortune rather than good standards.

2.3.2 Lack of partnership between learners, parents and instructors

There is considerable research on the influence of peers on driving behaviour. Social learning theories have been used to show that the presence of passengers, the behaviour of other drivers and the attitudes of peers and relatives can influence driver behaviour. For example, Fleiter et al. (2006) found that family members significantly influence speeding behaviour. They demonstrated that crash records for parents were correlated to teen crashes. Furthermore, it was also reported that low parental monitoring was related to less competent driving behaviour, traffic violations and crash among young drivers (Hartos et. al., 2000).

Parents can play a major supervisory role during the learning phase because they are in the best position to enforce learner’s driving restrictions and to instil safe behaviour (Mulvihill et. al., 2005). However the nature, quality, practice and partnership between the parents and young drivers during the learning phase has not been evaluated from a crash risk perspective (Simons-Morton and Hartos, 2003). Furthermore there is a lack of research examining how the instructor, parents and learner should interact to reduce the learner’s exposure to crash risks. On one hand, there is no comprehensive, practical and accessible means for parents to be
aware of and monitor the learner’s driving safety progress. On the other hand, instructors do not have the means to monitor the learner’s progress outside driving lessons or during unsupervised solo driving. Forsyth (1992) found that a balanced number of professional lessons and private instructions is the optimal type of training.

2.4 Driving Task Performance and Skill Acquisition

Driving performance can be represented by a set of rules describing actions which drivers take in response to a driving situation and/or situation change to achieve the purpose of the trip. The driving situation is a collection of variables outside the vehicle and this influences driver's vehicle manoeuvring actions. It includes (1) roadway geometry and conditions such as number of lanes, exit location and pavement status, (2) inter-vehicle driving conditions such as speed and distance of the surrounding vehicles, and (3) weather conditions such as fog and rain.

A driver's behaviour also can be understood in strategic level as well as tactical levels. Strategic behaviour is usually determined before the trip starts or far before the situation appears (deWaard, 1996). Trip route, preferred travel lane and lane changing locations belong to this category. Tactical level driving behaviour is determined in real time. It includes optional lane changing to achieve faster running speed or to avoid a certain danger.

Roadway geometry and conditions are the main factors influencing strategic driving behaviour (Crick and McKenna, 1992). Inter-vehicle driving conditions determine the acceleration of the vehicle, which can be represented using car following models and optional lane changing choice model for passing. These models belong to the tactical level driving behaviour (Crick and McKenna, 1992). Weather conditions influence both strategic level and tactical level driving behaviour with fog or heavy rain fall deterring trip demands. In a driving situation, they affect the driver's lane choice in the strategic level and cause a larger gap and lower driving speed for safety (Crick and McKenna, 1992). Therefore, car-following and lane changing behaviour in adverse weather conditions are different from the ones without them.
Drivers are not perfect in adjusting their speeds because of perception, estimation and action errors. Perception errors include measurement errors for distance or speed of the vehicle in front along with acceleration/deceleration. Estimation means the process of assessing the response to the perceived actions of other vehicles, i.e. when a lead vehicle starts braking the follower has to determine the amount of deceleration. Action errors refer to the error in implementing the derived response by controlling the mechanical components of a vehicle. With more time spent on the road driving under diverse conditions, this estimation will improve. Driving is a dynamic task which contains continuously changing variables related to vehicle and the environment. Information and information processing are one of the most important aspects of dynamic systems (Rauterberg, 1995).

### 2.4.1 Human Machine Information Processing Model

A basic Human Machine Information processing model can be considered as an input-output model. Human inputs certain information and the machine responds with an output. This information processing model can have different levels of detail and sophistication in how they account for the output. Common to them all is that they start by some external event or stimulus (process information or the evaluation of a routine action) and end with some kind of response (Hollnagel and Woods, 2005).

Figure 2.1 illustrates a simplistic human machine information processing model (Hollnagel and Woods, 2005) (pg.17). This figure shows the essence of a classical human-machine view. By using the simplest possible representation of each system as input, processing and output functions, it clearly shows the two main characteristics of the classical view. First, that the interaction is described exclusively as the exchange or transmission of input and output. Second, that humans and machines are described in the same fashion, using the finite state machine as a basis (Hollnagel and Woods, 2005).
Now, with the gradual transition towards more complex systems, the interaction between human and machine is multiplied. This created a change in paradigm to the classical human machine model. Here, human and machines could act and were acted upon by the stimuli. In the context of driving, the human machine model evolved to a Driver, Vehicle and Environment model, also known as DVE model. Figure 2.2 presents the information processing model for driving.

It shows the information exchange between human (i.e. driver), machine (i.e. car) and the stimulus (i.e. environment, road). Given the numerous variables that the driver has to handle in order to steer clear of any hazardous situation, this requires practice and experience.
Vehicle driving involves complex decision-making processes that are characterised by multiple, interdependent stages involving mappings between sensory inputs and control outputs. In order to attain some degree of expertise in such processes, a certain amount of practice is required (Pasquier and Oentaryo, 2008). This exemplifies the notion of decision-making as a form of cognitive skill that can be developed through practice. Cognitive skill involves the ability to effectively exploit one’s knowledge in the execution of cognitive processes (Anderson, 1981). In this regard, learning from examples has been established as a critical factor in facilitating the gradual transition from a novice’s slow and laborious execution to an expert’s rapid and accurate execution of a skilled behaviour (Tomporowski, 2003). Such a proficiency development is achieved through accumulation, recognition and refinement of the salient features from the past experiences (Anderson, 1981). Central to this development is thus the ability to acquire new knowledge (i.e. learning) and to retain that knowledge for later retrieval.

2.4.2 Hazard Perception

Hazard perception was defined by Crick and McKenna (1992) as the ability to identify potentially dangerous traffic situations. Evans and Macdonald (2002) define hazard perception as “the process whereby a road user notices the presence of a hazard” (p.93). Based on these definitions Haworth et al. defined hazard perception as:

"A hazard is any permanent or transitory, stationary or moving object in the road environment that has the potential to increase the risk of a crash. Hazards exclude characteristics of the rider or the vehicle, which are classed as modifying factors."

Hazard perception is an integral part of safe driving and research has shown that hazard perception training in novice drivers lead to improved performance in hazard perception tests (Evans and Macdonald, 2002). Researchers further mention the modifying factors that affect the level of risk of a hazard. An outcome of the hazard perception and responding process might be to change the level of the modifying variables – the response might be to slow down, which then changes the modifying variable of speed. Changes to the modifying variables might occur over a
longer timeframe, and this may be what happens in gaining experience and learning to drive more safely (Evans and Macdonald, 2002).

Researchers (Foss, 2009) mention driving as analogous to playing action sports such as baseball or soccer. Reflecting on the similarities of these sports to driving they argue that it is not difficult to recognise that hundreds of hours of practical experience in realistic “game-like” conditions are necessary for new drivers to reach a point where they are able to routinely and smoothly handle all but the most atypical driving situations. Most novices can learn simple manoeuvres such as starting, stopping, reversing and turning a vehicle within a few hours and become fairly good at them in a matter of days. But in the same way a person who can dribble and shoot a basketball is not ready to play a full speed game, a person who can handle a vehicle properly is far from being a full-fledged driver. A great deal more understanding and ability is needed to drive competently and safely. For example, drivers need to be able to routinely identify and react to a vast array of potentially hazardous situations, manoeuvre the vehicle in complex traffic situations, avoid being distracted at critical times and deal with passengers, to name only a few. Each trip involves unique situations that demand near constant attention and instantaneous decisions (Foss, 2009).

2.4.3 Risk Perception

The concept of risk is highly complex and Brown and Groeger (1988) defined objective risk as “the ratio between some measure of adverse consequences of events and some measure of exposure to conditions under which those consequences are possible” (p. 586). In other words, objective risk is a quantity to be estimated and the reliability of the estimate depends on the quality of the information underlying its calculation (Deery, 1999). For example, road traffic authorities often develop large databases of road crashes, usually expressed in terms of exposure or the size of the population under consideration. From this data, it is often reported that young drivers have a higher risk of crash involvement than their more experienced counterparts.

Risk perception is subjective and is based on the experience of risk in potential traffic conditions. Brown and Groeger (1988) suggest that these perceptions are
determined by two inputs: (a) information regarding the potential hazards in the
traffic environment and (b) information on the ability of the driver (and the
capabilities of the vehicle) to prevent those potential hazards from being
transformed into actual accidents. Thus drivers’ belief about their ability to handle
hazardous situations results from their self assessed driving ability.

People tend to be particularly resistant to the idea that they are at risk from any
particular hazard. Most people believe that they are in less danger than the average
individual, with a lower than average likelihood of dying from a heart attack, a lower
probability to be involved in a crash. For example, virtually all individuals believe
that they drive their vehicles better than the average person. This unreal optimism is
based on the information available and on a reasoning process that induces us to
think that the hazard in question is not a real threat, even though it may affect
people known to us. All of these perceptions influence people’s response to risk
(Fischhoff, 1995).

It can be concluded that there are several reasons why a driver might take a risk,
such as continuing to travel at a relatively high speed when a pedestrian steps off the
curb to cross the road (Stein and Allen, 1987). One reason could be that the driver
may exhibit poor risk perception but with experience this ability to accurately assess
the risky situation increases.

2.5 Importance of Visual Feedback in Driver Training

As mentioned previously, driver training is one of the interventions aimed at
decreasing the number of crashes that involve young drivers. Young drivers tend to
assess their own driving ability to be better than older drivers (Tronsmoen, 2008).
This over confidence on part of the young drivers is one of the factors affecting
novice drivers’ crash risk. Novice drivers need to gain greater self assessment skills
and understanding of the factors behind the risks. Effective feedback mechanism
should accompany other countermeasures such as persuasive communication
methods, with a view to changing attitudes and creating a greater understanding of
risk (ECMT, 2006). Young drivers’ skills are limited as compared to experienced
drivers. This limitation should be recognized by the novice drivers themselves.
Providing feedback about driving performance can increase the opportunity for
young drivers to experience the limitations of their driving abilities in a controlled and safe environment. It has been argued that effective feedback and making ensuring young drivers are aware of their limitations (self awareness) can address the issues of overconfidence and overestimation (AAMI, 2009)

Visualisation can provide valuable assistance for data analysis and decision making tasks (Moller and Troy, 2004). Figure 2.3 illustrates the information flow involved in the visualisation process, especially when the visualization tool is interactive. The way people perceive and interact with a visualisation tool can strongly influence their understanding of the data as well as the system's usefulness. Human factors therefore contribute significantly to the visualisation process and should play an important role in the design and evaluation of visualisation tools (Moller and Troy, 2004). The visualisations, in the form of driving patterns and assessments of driving tasks, can help in providing efficient feedback to young drivers regarding their driving performance. The visual feedback method will help to achieve one of the aims of this research.

- Designing an integrated visual interface regarding the driving tasks that assists driver trainers in effectively communicating high/low competency of manoeuvres performed by drivers.

Figure 2.3: The visualisation process (adapted from Moller and Troy, 2004)

Knowledge visualisation is an emerging field growing out of the cognitive and computer sciences with an objective to facilitate the creation and transfer of knowledge between two or more entities (Eppler and Burkhard, 2007). Differing from traditional information visualisation, knowledge visualisation is more than facts and graphs. The aim is to enable technology by allowing the correct transfer of complex insights, experiences, perspectives, and high level concepts from one entity to another (Burkhard, 2004; Burkhard and Meier, 2005).
The visualisation of the data can be improved by a number of methods including Moller and Troy, 2004):

**Interactive multiple views of data:** For different tasks and requirements, multiple visual representations of the data should be made available. Several representations may be visible at once using multiple view windows. If it is not possible to render a global view of the data set in which every element is precisely represented, it is possible to combine detailed, partial representations with vague, global representations. For example, in a medical imaging data set, slices and sub-volumes of specific areas could be combined with a rendered overview of the entire volume. The other important feature of visualisation is the interactive interface. Research has shown that manipulating objects relative to each other is easier than using absolute coordinates (Hinckley et al., 1994).

**Depth of focus:** Focusing effects can be used to highlight information by blurring everything except the highlighted objects (Kosara et al., 2001).

**Pre-attentive processing in visualisation:** Certain visual features (orientation, lightness, position, length, etc.) “pop-out” of an image, so that searching for them is very fast (Bruce et al., 1996; Ware, 2000).

**Encoding data with colour:** Visualisations can use colours to segregate or highlight objects. For example, a medical visualisation may show different organs in different colours and an air traffic control display may use colour to highlight potential collisions between aircrafts.

**Shape perception:** Contours play an important role in shape perception (Peters, 2000). 3D shape may be more easily interpreted from cartoon-style drawings than from photorealistic images. For this reason, there is current interest in developing non-photorealistic rendering (NPR) styles for continuous model visualisation (Peters, 2000). For volume data, contour rendering (Csebfalvi et al., 2001), pen and ink style rendering (Treavett and Chen, 2000), and volume rendering with NPR effects (Rheingans and Ebert, 2001) have been explored.

These visualisation systems could play several roles (Moller and Troy, 2004):

- Visually represent data to enhance data analysis.
- Visually display users’ mental models, interpretations of the data, ideas, hypotheses and insight.
• Help users to improve their mental models by finding supporting and contradictory evidence for their hypotheses.
• Help users organize and share ideas.

Until now, research in visualisation is almost exclusively devoted to the first objective (Muller, 2004). Research into the other objectives has not been greatly explored and could make a valuable addition to data analysis tools. The current research will use visualisation techniques to visually represent the driving data and assessment of the driving tasks. Furthermore, the visual representation of the driving tasks will help its users (i.e. driver trainers and trainees) to gain insight and discuss driving aspects that need improvement.

The techniques mentioned above for improving visualisations are not intended for improving realism. Realism is not too relevant to visualisation because the goal of visualisation is to represent data, not to display a realistic image of the world. Eventually, the goal of introducing driving tasks’ visualisation in the feedback process during driver training is to enhance the drivers’ understanding of their decision making and driving behaviour (i.e. self assessment).

2.6 Summary

This chapter provided a comprehensive literature review on driver education discussing the basic approaches (i.e. Engineering, Enforcement and Education) to any problem related to the public. These approaches were presented in the driver training context.

This chapter initially highlighted the novice driver problem and discussed the multiple factors that expose young drivers to crashes. It discussed the existing differences in training and educating of the driver. Emphasis on the assessment of the training programs was also presented. This was followed by brief views on the importance of self assessment on part of the driver. It was pointed out that the knowledge gained regarding drivers’ own limitation is of utmost importance.

This chapter accomplishes one of the aims of this thesis by identifying the shortcomings of the existing driving training programs. It emphasized the lack of driver training standards. Currently, driver training is based more on commonsense
rather than scientific knowledge. Moreover, the lack of communication between the learner drivers, teachers and parents was also discussed. The final sections of this chapter discussed driving behaviour which compared the classical human machine interaction with an evolved human, machine and environment interaction model. It further presented the importance of hazard perception and risk perception in a complex driving scenario. It stressed the fact that risk perception is a subjective phenomenon and is based on the driving experience of the driver and knowledge about the drivers’ own limitations. The usefulness of an emerging field, called knowledge visualisation for facilitation in the creation and transfer of knowledge between two or more entities, was also presented. The next chapter reviews the multiple Advanced Driver Assistance System (ADAS) that are utilised for monitoring variables involved in driving. It will also discuss the synchronisation of multiple sensory data (from driver, vehicle and environment) to provide a holistic view of the driving scenario.
The previous chapter discussed the importance of driver education in detail. It presented the issues related to novice drivers’ overrepresentation in crashes. It also highlighted the importance of driver skill acquisition and hazard perception. The lack of effective driving training programs, self assessment of the driver and technological interventions for improving these assessments were also discussed. This chapter (3) will review the different technologies and systems that enable effective monitoring of the driving tasks, by analysing information from driver, vehicle and the environment. Along with this, the current chapter will discuss sensors that enable the safety systems to help to mitigate driving hazards.

The driving situation is a collection of external factors outside of the vehicle-driver unit, and these external factors influence vehicle control. It includes (1) roadway geometry and conditions such as number of lanes, exit location and pavement status, (2) weather conditions and (3) other road users. These external factors combined with the vehicle control and driver behaviour make driving a complex task. Advanced Driver Assistance Systems (ADAS) are designed to help improve driver safety by enhancing driver situation awareness in dangerous situations, passive and active mitigation of hazards.
This chapter will introduce and review different types of intelligent driver assistance and warning systems. It will survey different ADAS functionalities that are used for monitoring the variables involved in driving (driver, vehicle and environment). Emphasis will be given on the use of ADAS in a fused manner to comprehensively evaluate driving performance. Section 3.1 presents the multiple types of ADAS that are being used to enhance driver safety. This is followed by limitations of existing driver assistance systems and this section (3.2) also presents the key factors involved in a successful assistance system. Section 3.3 highlights the different types of sensors that are used to monitor drivers in order to assess their behaviours. This section also mentions the importance of synchronisation and integration of data from multiple sensors for a comprehensive view of driving scenario. The last section (3.4) concludes this chapter.

3.1 Advanced Driver Assistance Systems

Driving is composed of three major categories of activity from a task/function analysis perspective: vehicle control, navigation and collision avoidance, all of which contribute to overall complexity of the driving task (Hancock and Parasuraman, 1992). With experience and practice, most drivers can perform these tasks relatively well. However, with the increase in environmental complexities, the driving task becomes more and more demanding for the driver. These environmental complexities increases the number of risks that drivers encounter which demands the need for Advanced Driver Assistance Systems (ADAS), that can assist drivers in performing driving tasks safely. ADAS provide support in maintaining control, as well as prevention of crashes and navigational assistance. ADAS which prevent collisions by informing the driver are also known as intelligent driver warning system.

There are many kinds of ADAS, depending on the level of assistance they provide to the drivers. They can be broadly categorised into active and passive safety systems.

3.1.1 Passive and Active Safety - ADAS

Passive safety systems can further be divided into two categories: (1) Information Presentation and (2) Passive mitigation of hazards (Carsten and Nilsson, 2001; Inro,
Passive safety provides information obtained from the sensor to the drivers for assisting drivers though it does not directly mitigate a hazardous situation. Rather, it provides detailed information of the surroundings in an effort to increase drivers’ perception and awareness. The information presentation systems include night vision systems that aid drivers in the dark by creating a visual image of the road way based on the thermal imaging technology and infrared sensors. This information is usually provided on a Heads-Up Display (HUD). This information presentation enhances the situation awareness of the driver by aiding in their perception of the driving environment (Carsten and Nilsson, 2001). Systems that provide passive mitigation of hazards provide additional aid to drivers by providing assistance for both recognising the driving environment and judging the criticality of hazards by providing warning alarms. These are considered passive safety systems, as they only warn drivers but do not actively mitigate hazards, unlike active safety systems. Examples of passive intelligent warning systems include: Forward Collision Warning (FCW) systems, rear end collision warning system and intersection collision avoidance system (Inro, 1999). These passive hazard mitigation systems aid in comprehending the driving environment by alerting drivers to hazards through the use of alarms. Other passive systems include airbags and seatbelts which help to protect the driver and passengers from injury when a crash occurs. Figure 3.1 below presents the different classifications of the safety systems as well as the examples of ADAS systems, for both active and passive safety systems

![Figure 3.1: Classification of Advanced Driver Assistance Systems according to Level of Driver Assistance (from Burns, 2001)](image)

The level of assistance that the ADAS provides can range from intervening and taking partial to full control (Sheridan and Verplan, 1978). Active safety systems also
called active intelligent warning systems are intervening assistance systems that have a higher level of automation and lower level of driver control (Inro, 1999). These systems provide more assistance to the drivers and mitigate hazards actively without any input from the driver. An example of such a system is an Adaptive Cruise Control (ACC). ACC detects obstacles in front of the driver and intervenes by using evasive measures such as applying brakes to change the car’s speed so that the following distance does not exceed a certain threshold. Hence, active safety systems enhances drivers’ situational awareness by helping drivers anticipate and take action to mitigate the hazard by not just providing warnings, but also by taking partial control of the vehicle. Another example of active safety system is Electronic Stability Program (ESP) or traction control that prevents the wheels to skid thus allowing the driver to steer clear of danger (Hancock and Parasuraman, 1992).

### 3.1.2 ADAS for Monitoring Driving Events

In the past, a number of prototypes of intelligent vehicles have been designed, implemented and tested on the road. The design of these prototypes was preceded by the analysis of solutions derived from similar fields of research. Robotics, artificial intelligence, computer science, computer architectures, telecommunications, control and automation, signal processing are just some of the principal research areas from which the main ideas and solutions were first derived (Bertozzi et. al., 2002).

Many intelligent vehicles have used a number of solutions from the field of robotics. However, the difference between robots and vehicles is that vehicles are controlled by drivers. Therefore, for designing an intelligent driver focused system, the human perspective should be taken into account. It is important for the intelligent driver related technologies to evaluate the psychomotor, perceptual and cognitive skills of the driver, because 90 percent of crashes are due to human errors (ECMT, 2006). By adding human in the driving loop of a system, the perception and response of a warning to a person becomes important. This is a complex issue because there are a lot of factors that influence human perception, interpretation and response. Researchers in (NHTSA, 2007) have identified the key points that should be thoroughly considered before implementing an effective warning system.
Currently, the advanced driver assistance technologies in the market include:

- Ultrasonics, Radar, Lidar, infrared, cameras, sensors
- Optics based obstacle detection
- Occupant detection systems
- Active/Reactive pedestrian safety systems
- Pre-crash sensing systems
- Road sign recognition systems
- Lane departure warning systems
- Blind spot detection systems
- Self parking systems
- Night vision systems
- Adaptive Cruise control systems
- Intelligent Speed Adaptation.

However, intelligent systems can be used for a variety of different purposes such as:

- Informing/warning the driver in advance prior to a possible collision (active safety).
- To reduce the severity of crashes (passive safety).
- To train the driver by informing them if an illegal/unsafe driving manoeuvre was performed. A little research has been done so far for this purpose.

The term “convenience system” came into being in the late nineties when auto companies were ready to offer driver assist systems (Bishop, 2005). This term changed to “safety systems” when legal implications and performance requirements of these systems were taken into consideration (Bishop, 2005). These safety systems are now becoming more pervasive as they are applied to commercial vehicle and public transit buses. Pervasiveness and affordability are the prime factors in long term success of ADAS. Applications such as adaptive cruise control, blind spot detection must provide frequent and obvious benefits to drivers for them to experience value for their money (Bishop, 2005).

Along with providing assistance to the drivers, another benefit that current ADAS can offer is to assess how well a driver is driving. For example, lane positioning
system detects the distance of the vehicle from the lanes and by comparing the speed during the lane change for an expert driver and a novice driver, lane changing manoeuvres can be assessed. But in order to have an intensive evaluation of the driving scenario, the holistic data from ADAS pertaining to driver, vehicle and environment (DVE) has to be observed.

To date there have been a number of systems that have focused individually on the three main aspects of intelligent vehicular technology namely vehicle dynamics, driver and the road. Some effort in fusing the information has been accomplished (Apostoloff and Zelinsky, 2003) and (Andreas et al., 2007) but there has not been any integration of information to verify if a certain driving manoeuvre was performed in a high or low competent manner. The results of this evaluation can further be utilised for training the young driver. Thus ADAS sensory information has the ability to be initially used for designing an evaluation system for the driving tasks and later providing feedback for training purposes.

### 3.1.2.1 Driver Vehicle Environment (DVE) Model

In order to develop efficient and effective counter measures against crashes, it is necessary to understand the full context of driving. The three main components of a driving situation are: Driver, Vehicle and Environment (DVE model). These three components are discussed below in further detail. For any effective driving crash counter measure, the complex dynamics of the various events and interaction of the DVE model has to be fully taken into account. An effective solution must integrate and synchronise the information gathered from the DVE in order to make a useful decision. This is a complex task since efficiency (real time), accuracy and robustness are paramount in safety critical applications. Any proposed solution must take a systematic approach by assessing the interactions of all the three components involved in driving (i.e. DVE).

- **Environment**

  The solution for an advanced driving assistance system or an autonomous car, begins with acquiring information about the road and any possible obstacles (vehicle, pedestrian, animal) on it. As with all other computer vision applications, robustness is an issue that is difficult to solve. For a system to be robust, it has to work on varying light conditions that means intelligently removing unwanted
shadows. It also means that a system should be able to work in different weather conditions i.e. rain, fog, snow etc. It should also be effective in partly occluded road or lane markings because of a vehicle or a shadow.

**Technological Examples**

The assistance systems have evolved from Generic Obstacle and Lane Detection (GOLD) (Broggi, 1999) and Rapidly Adapting Machine Vision for Automated Vehicle Steering (RALPH) (Pomerleau and Jochem, 1996) to off-road autonomous driving systems (Bertozzi and Broggi, 1998) and context aware warning systems (Mohan et. al., 2007).

Along with the lane and obstacle detection in the vehicle’s surroundings, there has been considerable breakthrough in detecting and recognizing the road signs. Support vector machines have been used in (Maldonado-Bascon et. al., 2007) for effective detection and recognition of the road signs. A complete description of the methodology regarding detection and recognition of road signs can be found in (Maldonado-Bascon et. al., 2007). PReVENT, which is a collaborative project between the European automotive industry and European commission has contributed substantially towards road safety by developing and delivering crash preventive safety applications and technologies (Austroads, 1995). PReVENT has worked on areas including digital maps, sensors for collision mitigation, lane keeping, integration of multi-sensory data, 3D sensor technology for obstacle detection and classification and vehicle-to-vehicle communication.

- **Vehicle**

Another important aspect in intelligent vehicles is the ability for the system to monitor vehicle dynamics before deciding on a situation. For example there is no need for the system to inform the driver of a possible collision if he/she is going at 10km/hr and scanning the road. This shows that for an effective advance warning system, it is necessary to compute context sensitive information as well before declaring a situation as a possible collision course.

**Technological Examples**

Different telemetry devices such as Global Positioning System (GPS) and accelerometers are now being used as tools to determine the vehicle position, motion and road quality. In addition, location, velocity and acceleration are the information that is required for effectively judging the road scenario. Adaptive
Cruise Control (ACC) and Antilock Braking Systems (ABS) are also technological examples that monitor vehicle dynamics.

- **Driver**
  As mentioned earlier, driver error is a common contributing factor in crashes. Therefore, an important aspect of safe driving is that the driver acts appropriately and efficiently whilst driving. An intelligent driving system should assist drivers to improve their related physical and psychomotor events during driving. Extensive research has revealed that it is not so much the lack of basic driving skills that cause crashes, but higher order skills. These higher order skills deal with risk perception, situational awareness, risk acceptance and self assessment (Jose and Mayora, 2008). A driving system, based on ADAS, training or a combination of both, that can improve drivers’ higher order skills is still needed. Furthermore, researchers have examined the effect of different factors that lead to driver distraction (Green, 2004).

Driver distraction has been studied in detail by ergonomic scientists (e.g. Trick et. al., 2004). The emphasis has been on determining the driver’s mental workload involved in manoeuvring through a particular driving scenario. Nowadays, in addition to observing and reacting to weather, road, vehicle, and traffic conditions, drivers may use technologies such as:

- Entertainment systems such as radio, CD or MP3 player, movie screen
- Telematic systems for navigation, email, mobile phones, or traffic information
- Driver assistance systems such as cruise control or collision warning.

Although some of these technologies are designed to improve safety, drivers may sometimes divert their attention from focusing on the road to glance at display, operate controls e.t.c. This distraction from the road may leads to a possible collision. In order to avoid this situation, researchers have identified a concept of selective attention as a key construct. Below are examples of some systems that have already been built for driver monitoring.

**Technological Examples**

FaceLAB is a tool that focuses on driver’s face and monitors the eye gaze, blink rates and eye closure (Waard, 1991). This can be further used to monitor driver attentiveness, gaze direction, fatigue etc. (Gavrila et. al, 2004; Bertozzi et. al., 2002
and Andreas et. al., 2007). Along with this, Volpe center has developed a system named Safety Vehicle using adaptive Interface Technology (SAVE-IT). This system represents a viable proof-of-concept vehicle capable of reducing distraction-related crashes whilst enhancing the effectiveness of collision-warning systems (NHTSA, 2004). Volpe centre is further focused on exploring and evaluating technologies to measure driver distraction, and developing decision rules to prioritize in-vehicle information demands on the driver. Other researchers have developed a system that takes the driver behaviour into consideration while performing driving manoeuvres (Andreas et. al., 2007; Apostoloff and Zelinsky, 2003). These researchers used cameras and multiple types of sensors to determine the driver’s feet, body movements and facial feature recognition.

By using the Human Computer Interaction module that acts as a decision making module, Zhao et. al. (2006) and Bertozzi et. al. (1996) have tried to contextually evaluate whether warnings should be given to the driver at a certain time. By evaluating the future situation and the intended driver action, their system acts as an advance warning system.

### 3.2 Limitations of Existing ADAS

Various ADAS have been used in the past to assess particular aspects of driving and detect road objects in the environment such as road signs, lane markings, pedestrians and distance to a car ahead (Aufrere et. al., 2003; Wöhler and Anlauf, 2001). Data loggers are a particular type of ADAS device that gathers information about vehicle dynamics. Significant advances have been achieved in detecting driver behaviours such as head movement, eye blinks, eye gaze or steering grips (Ji and Yang, 2002). Some systems integrate lane marking detection with the gaze focus of the driver (Apostoloff and Zelinksy, 2004).

Intelligent driver warning systems have to be robust and reliable stand-alone systems in order to assist drivers and they should not add to the complexity of a driving task. Research has shown that the auditory modality generally seems to be best method for conveying warning signals since it does not overload the visual channel which is very important for driving tasks (Tijerina et. al., 2000; Liu, 2001).
This emphasises the importance of design standards whilst creating driver warning systems.

Whilst driving, there is a high demand on drivers’ the visual faculties as driving tasks mainly involves tracking and monitoring (Liu, 2001). Therefore it is important that multiple alarms from different warning systems do not occur at rapid intervals. One solution is to assign priorities to the hazards based on safety relevance to drivers (Neale and Dingus, 2006). Thus a higher priority warning will be given more precedence over a lower priority warning. The second issue with the existing ADAS is confusion over the meaning of alarms caused by different warning systems. A unique alarm for each different type of hazard might result in too many alarms, thus making it difficult for drivers to recognise and remember the meaning of each alarm resulting in drivers’ cognitive overload. Whenever the driver misinterprets an alarm, they may commit an error or respond inappropriately to the alarm. This can result in the warning system being useless and lead to degradation in driving performance. Therefore it is necessary that warning systems should assist rather than confuse the driver (Neale and Dingus, 2006). In addition, for any effective ADAS, it is necessary that these systems provide efficient (real time), accurate and robust results since these factors are crucial in safety critical applications.

Aside from the issue of accuracy, robustness, warning prioritisation and confusion due to lack of comprehension for the meanings of alarm, another issue related to ADAS exists. This issue is their dearth of utilisation in a driver behaviour assessment context. Existing ADAS are only able to give a partial picture of driving behaviour (i.e. different systems provide information regarding lane keeping, over speeding, following distance, driver distraction). Currently there is no system that comprehensively integrates vehicle dynamics, driver psychomotor behaviour and environmental information to effectively monitor driving manoeuvres. In order to successfully solve problems using ITS technologies, the whole driving context has to be taken into consideration by monitoring all variables associated to DVE. Once the variables from DVE are integrated, the comprehensive data can be used for monitoring as well as assessing the driving manoeuvres. The assessment of the driving manoeuvres can eventually be used to educate drivers about the safety of their performed manoeuvres.
Advances in ADAS and intelligent transportation systems (ITS) can improve driver training by enabling objective recording of the types of experiences a driver accumulates, and identifying areas that have not been well practised. The use of ADAS in driver training offers the potential to allow tracking and feedback during the whole learning period including instruction, accompanied driving and during solo driving.

3.3 Assessing Primary Driving Tasks

Researchers have defined the primary driving tasks as functions that are central to driving and without which moving a vehicle to a destination safely would not be possible (Wheeler et. al., 1996). The primary driving tasks are divided into three broad categories: navigation and routing, guidance and manoeuvres, and control (Broggi, 1998). A successful execution of all these tasks is necessary for the driver in order to drive safely. Researchers in (Elander et. al., 1993) have argued that crash possibility is related to driving performance. In fact, almost 90% of road crashes are attributable to driving error (Shinar, 1978).

Many current intelligent systems focus on warning drivers by predicting the trajectory of an oncoming obstacle relative to the current vehicle (Bertozzi et. al., 2000; Wilson and Dickson, 1999). Only a few of these systems evaluate the situation (by acquiring sensor data about driver, vehicle and environment) and make the driver aware of relevant knowledge extracted from sensors (Manubhai et. al., 2007). As mentioned before, if prioritization of the warning system is not appropriately refined, it could become a distraction for the driver.

Responding to a risky scenario during driving requires a time critical response. This response is usually dependent on the cognitive capacity of the driver. A point reiterated in literature critical of driver training is that more in-depth analysis of the driving task and traffic situations taking into account the cognitive skill aspect such as hazard perception, risk perception, decision-making skills, self-monitoring processes, learning styles, motivations and risky attitudes may improve training (NTSB, 2003; Watson, 2003).
As mentioned previously, driving is a complex task and it requires a lot of information processing in critical time. The driver has to seek relevant information, evaluate or process the information and then respond appropriately. The driving task has been classified into three stages (Broggi, 1998) and as shown in figure 3.2, these are based on the time each task/stage is required to be performed. The levels are (Broggi, 1998):

- **Strategic Level**: Requires long time to perform and is considered a high level task, e.g. choosing itinerary.
- **Manoeuvring Level**: Requires seconds to perform and includes reaction to local situations, e.g. speed adjustment, following distance, turning, overtaking.
- **Control Level**: Requires milliseconds to perform and includes handling the vehicle, e.g. controlling the position of the vehicle on road.

These levels are crucial in avoiding road crashes. Some contributing factors to road crashes are related to the control and manoeuvring of the vehicle (Waard, 1991), such as failure to correct vehicle trajectory or inability to brake in time during an emergency situation.

![Figure 3.2: Driving Levels](image)

### 3.3.1 Monitoring Driving Events Using Sensors

Since 1980, car manufacturers have been developing computer based in-vehicle devices (Bertozzi et. al., 2002). Over the years, different type of sensors such as radars, GPS, accelerometers, gyroscopic sensors and cameras have been used extensively in Advanced Driving Assistance Systems (ADAS). ADAS consists of software systems that are implemented using physical sensor(s). For example,
navigation systems are built upon underlying GPS hardware and lane and obstacle monitoring are built upon cameras and/or laser scanners.

Currently, researchers are using in vehicle mounted cameras to measure different aspects of driving experience i.e. fatigue, monotony, body movements etc. Many current intelligent vehicle solutions use radar and lidar technologies. Although these technologies are robust in varying weather condition, the sensor data acquired from these technologies is limited compared to the information retrieved from a camera. A successful solution will be to combine the benefits of multiple sensors such as GPS, radar, accelerometers, lidar and cameras.

3.3.1.1 Vision based sensors - Cameras
Computer vision has been used in the past couple of decades to provide solutions to the problems in the field of autonomous agents (Broggi, 1998). Researchers have been working on different algorithms for effective detection of road boundaries and obstacles (Broggi, 1998), (Bertozzi et. al., 1996) and (Roening and Haverinen, 1997). A descriptive study has been undertaken in (Broggi, 1998) regarding the use of computer vision in Intelligent Transportation Systems. A drawback of machine vision identified is that it does not extend sensing capabilities besides human possibilities (e.g., in foggy or rainy conditions), but can, however, assist the driver in case of a mistake, e.g., lack of concentration or drowsiness.

Machine vision has evolved over the past few years to solve problems such as pedestrian detection, obstacle and lane tracking for more robust and reliable autonomous vehicles. Different algorithms utilizing both single and stereo cameras have been used to reliably solve these problems and computer vision has also been used to monitor drivers (Mitrovic, 2005; FaceLab, Oliver and Pentland, 2000).

Computer vision is a branch of artificial intelligence that focuses on providing computers with the functions typical of human vision. To date, computer vision has produced important applications in fields such as industrial automation, robotics, biomedicine, and satellite observation of earth (Picardi and Jan, 2003). Integration of computer vision in intelligent transportation systems has helped solve many problems relating to object identification and classification.
Intelligent transportation systems include problems that require multidisciplinary efforts and computer vision is one of the solutions. Until now, computer vision has been used in the field of ITS to solve problems such as lane detection, obstacle detection, driver body movements, blind spot monitoring etc.

- **Night Vision Systems**

Night vision systems were originally developed for military operations and were adapted by automotive market during the 1990s (Bishop, 2005). The first system was introduced in Cadillac. These first generation night vision systems employ an infrared (IR) camera operating in the far infrared region (over 1000 nm). The forward range of these sensors is around 500m (Bishop, 2005).

The Near-IR is projected from the vehicle and reflected energy is received and processed. Near-IR is far superior to thermal night vision (far-IR) systems, because near-IR provides more natural looking images. The near-IR is not visible to the human eye and therefore, oncoming drivers are not affected by it. The night vision systems extensively increase the ability of the driver to perceive the oncoming obstacles extensively. In the absence of a night vision system, a pedestrian would be visible at a very late stage in the field of view of the driver. It will not provide the
driver adequate response time and can lead to hitting the pedestrian or losing control of the vehicle. A night vision system will definitely enhance the response time for the driver to avoid the obstacle.

Some examples of night vision systems previously or currently in use are: Visteon’s driver vision at night, PSA night vision (e-Safety, 2002) and Bendix XVision (Bendix).

### 3.3.1.2 Radar and Lidar Based sensors

Automotive radar devices are appearing in many transport and luxury passenger motor vehicles used in different parts of the world. The following automotive manufacturers are known to include automotive radar devices in their vehicles: Daimler-Benz, BMW, Jaguar, Nissan, Toyota, Honda, Volvo and Ford. Fujitsu, an electronic component manufacturer, is known to be producing semiconductor devices specifically for automotive radar systems (Bishop, 2005). The key radiofrequency aspects of the automotive radar component are listed below:

<table>
<thead>
<tr>
<th>System type:</th>
<th>Pulse</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency Band:</td>
<td>76 – 77 GHz (varies)</td>
</tr>
<tr>
<td>Emission bandwidth:</td>
<td>Up to 500 MHz</td>
</tr>
<tr>
<td>Antenna beamwidth (max):</td>
<td>4° elevation, 15° azimuth</td>
</tr>
</tbody>
</table>

The radars are currently being used for a number of tasks including Adaptive Cruise Control, collision warning, pedestrian detection, blind spot monitoring, lane change assistance, parking assistance etc.

LIDAR (Light Detection and Ranging) or Laser scanners have been used in scientific research for several years and have recently been used in active safety systems. Currently there is a lot of focus on improving the performance of laser scanner for driver assistance systems.

Lidar is essentially a rotating infrared light beam (Bishop, 2005). Using this light beam, the time of flight measurement is used to detect the contours of objects in the vicinity of the vehicle. The time of flight measurement provides information on
the distance to the object. Based on the information retrieved, objects are extracted and classified, along with their distance, speed and acceleration. High performance version of these sensors contains four scanning devices but the automotive unit uses just one scan plane for easy integration with the vehicles. The most widely used LiDAR is produced by the automotive company named Ibeo (CSIRO, 2001).

### 3.3.1.3 Other sensors

Apart from the vision, radar and laser based scanners used for monitoring driving events. Other sensors that assist in monitoring drives include accelerometers, rain sensors, GPS and sensors to acquire vehicle dynamics. All these sensors assist in creating complex advanced driver assistance systems.

### 3.3.2 Sensors and Data Synchronization

As mentioned previously, in order to successfully solve the driving problems utilising ITS, the whole driving context has to be taken into consideration. The above discussions present each component (i.e. driver, vehicle and environment) individually. However, in order to assess driving manoeuvres in a comprehensive manner; an integration mechanism for variables related to DVE is needed. The goal of data integration is to combine data from various sources, in several formats and at different frequencies into meaningful inferences.

Wald (1999, p.1191) advanced the definition of data integration as:

"Data Fusion is a formal framework in which are expressed means and tools for the alliance of data originating from different sources. It aims at obtaining information of greater quality; the exact definition of ‘greater quality’ will depend upon the application”.

The concept of data integration goes back to the defence research community of the 1980’s. In the UK, the defence establishment considered this to be a process comprised of collection, collation, evaluation and dissemination (Mirza, 2006). A brief description of activities in the various phases is provided below:

- **Collection**: Information from electronic or human sources is gathered and reported.
- **Collation**: Adjacent reports are combined or compressed for next stage fusion.
• **Evaluation** - Intelligence is fused, either through some form of automation or via human interpretation, to make informed decisions at the next stage.

• **Dissemination** - Distribution of intelligence reports to commanders for asset deployment.

Data integration is the process of collecting, organising and integrating raw and processed data from multiple sources and producing meaningful conclusions from these data (Luo and Kay, 1989). As previously mentioned, a few systems have been designed to combine data from multiple sensors such as sophisticated systems for intersection assistance (Heenan et. al., 2005), congestion assistance, collision warning and mitigation, and lane change assistance. These systems have the availability of multisensory data along with the means to store and process this data provided through developments in architectures and communication (Shooter and Buchanan, 2001). This data synchronisation from various sensors is necessary in order to have a holistic view of the driving scenario. However, to our knowledge, there are no ADAS that assesses driving manoeuvres in a comprehensive manner. Such assessment systems can ultimately be used to train drivers by providing them a comprehensive view of their performed driving manoeuvres.

None of Zhao et. al. (2006), Bertozzi et. al. (1996), DriveCam or VigilVanguard systems determine comprehensively if a driver was driving safely or not. A driver safety program designed by SACNIA provides real-time support system that coaches the driver with hints and feedback to refine the driving style (Scania, 2010). The issue is that this SCANIA system only monitors the acceleration and braking for reduced fuel consumption. As previously stated, in order to comprehensively tackle road safety issues, a complete and integrated framework is needed that will include and examine all the parameters that influence driving (i.e. cues related to road, vehicle and driver). Even though some efforts have been invested (though mostly for effective scanning of on-road objects) in simulator training of older drivers (Lavallière et. al., 2009; Beauchemin et. al., 2009) after integrating multisensory data yet these systems do not possess the ability to automatically assess driving manoeuvres along with limited sensor choice. Another issue is the use of driving simulators for training. Despite the fact that there is a minimal possibility of an injury, simulators do not completely provide a true feeling of immersivity in the
scene (Arjona and Menendez, 2005) thus affecting the realism of the driving scenario. Through enhancing the data acquisition tools and technologies that have been used in the past on a real world driving scenario, an effective driving monitoring system can be designed. This system will effectively integrate the data acquired from multiple cameras and sensors over time and evaluate the performance of the driver in an automated manner.

For synchronization / integration of information from multiple sources in real-time, RTMaps can be used (RTMaps). RTMaps accurately dates all data at their time of acquisition. This dating process provides a complete data flow control. This can then be used during the data processing and replaying. It makes it possible, in particular, to control priority flows and to synchronize the data to be fused. During the tests, situations and behaviours can be recorded and analysed later. Reproducing a situation is thus possible. An intuitive graphical interface, associated to a reliable and robust technology, makes this tool efficient for Research and Development (RTMaps).

Figure 3.4 shows that heterogeneous data such as the speed of a car, steering wheel angle, foot movement around the brake, head and eye movement and input from the road environment being recorded.
RTMaps provides the scalability to integrate softwares such as faceLAB to monitor the driver body movements as well. This synchronised data relating to driver, vehicle and environment can then be used for complete assessment of the driving manoeuvres. These assessments can eventually be used to educate drivers about the safety of their performed manoeuvres.

3.4 Summary

Over the past years, a number of active and passive safety features have been introduced. Even with these safety features the number of injuries and fatalities in crashes is alarming. One of the reasons for the increase in the number of crashes, even with added safety features is that competency of drivers has not necessarily improved. In the USA, investigation has determined that in 70% of all crashes the primary cause was the driver and in another 20% driver error is a major contributing factor (Aufrere et. al., 2003). This implies that driver perception of a particular
driving hazard remains a key factor impacting road safety. Therefore, for developing useful measures to tackle road safety issues, a complete and integrated framework needs to be developed that will include and examine all the parameters that influence driving (i.e. cues related to road, vehicle and driver). Therefore, for the reliable resolution of road safety issues, multidisciplinary research efforts are required.

This chapter presented an insight into the various technologies and techniques that are used to solve issues surrounding the field of Intelligent Transportation Systems (ITS). Along with this, it provided the different safety systems that monitor parameters related to driver, vehicle and the environment. It mentioned the limitation of existing Advanced Driver Assistance Systems (ADAS) in the context of comprehensive driving assessment. This chapter discussed the need for an intelligent driver training system in the light of current solutions provided for enhancing road safety.

This review presented two main kinds of driver assistance systems (i.e. active and passive) and their examples. It described the three main components involved in driving (i.e. Driver, Vehicle and Environment - DVE) and the different ADAS that assist in monitoring each driving component. This chapter later highlighted the limitations of existing ADAS systems and emphasised the need for developing a system that could detect and assess driving manoeuvres. In the final sections of this chapter, a complete driving context was explained and the need to consider the entire driving context (i.e. interaction between the driver, vehicle and environment) for solving the issues for future safety systems was presented. It reviewed multiple sensors that can be combined to monitor the driving task more comprehensively. Along with this, the final section of this chapter discussed multisensory data integration that will effectively merge the data acquired from multiple sensors over time and evaluate the driver performance. The following chapter will review the different mathematical models that have been used to monitor driver behaviour and manoeuvres for assessment of driving performance.
Chapter 4

Performance Assessment

The previous two chapters presented the concept behind driver education and also the current technologies that are used to monitor driving events related to driver, vehicle and environment (DVE) respectively. The previous chapter (i.e. chapter 3) also discussed the need to view the three driving components (i.e. DVE) in a holistic manner for a comprehensive assessment of the driving performance. In this chapter, the different mathematical models used to assess driving performance will be presented.

This chapter establishes how driver performance has been modelled in the literature, with emphasis on the difference in modelling for inexperienced and experienced drivers. The chapter begins with section 4.1 that looks at different cognitive processes involved in driving. It also defines high and low competent driving practices that will be used to assess driving in this thesis.

Section 4.2 highlights the multiple criteria that are used to measure low or high competence for driving manoeuvres. This leads to a review of different approaches that can be used in assessing driving performance while drivers’ attempt the manoeuvres. Sections 4.3 until 4.6 further reviews the selected approaches namely, Hidden Markov Model (HMM), Neural Networks (NN), Generalised Linear Models (GLMs) and Fuzzy logic, and discusses their design in view of assessing
driving performance while undertaking manoeuvres. A summary of this chapter is presented in section 4.7.

4.1 Driving Behaviour and Performance

The distinction between driver performance and behaviour is central in understanding the driving task since normal driving is considered a self-paced task (Fuller, 2005). Driver performance is related to what a driver can do while driver behaviour is what a driver does (Evans, 2004). Driving performance depends on the driver’s knowledge, motor skills, perceptual and cognitive abilities while driver behaviour is what the driver chooses to do with these attributes.

Developing assessments for training purposes that accurately reflect driving performance depends upon the formulation of clear performance criteria. Performance criteria should encompass observable and measurable driving tasks as well as their corresponding standard. As presented in the GADGET matrix (see Table 2.1), the drivers’ task is described as a functional hierarchy. The higher level provides meaning to the lower levels and guides the decision that drivers make in a traffic situation. This hierarchical approach helps in understanding more clearly what competencies a driver need (Hatakka et. al., 2003). Fuller (2000, p.49) defines competence as the driver’s attainment of a range of skills broadly described as roadcraft, a concept which includes control skills, ability to read the road (hazard detection and recognition) and anticipatory and defensive driving skills. These competency standards define performance and Sabourin (2004) suggests that measuring competency requires:

- A performance-oriented training system based on clearly defined tasks which comprise the task to be learned; and
- A systematic evaluation of competence which illustrates how well the task is accomplished.

Therefore increased control of driving tasks and vehicle implies higher competency. Given that driver trainers are more proficient than novice drivers, their driving performance should result in lesser loss of control of the vehicle or driving task hence portraying a highly competent driving skills.
Driver’s performance is initially constrained by characteristics of the driver such as information processing capacity or sensation seeking level, speed, reaction time and motor coordination. Built upon these characteristics are knowledge and skills arising out of training and experience (Fuller, 2005). Together, these biological characteristics and acquired characteristics through training and experience determine the maximal competence limit of the driver. However, this competence is vulnerable to other human factor variables such as the drivers’ capability in resource allocation or interacting elements (environmental factors, other road users, vehicle operational features and elements of task demand). All these capabilities become more naturalised with experience as drivers’ ability to anticipate risks increases. This highlights the fact that driving performance can be categorised into a range of competencies (i.e. between “low” and “high” competent driver). These concepts are further discussed in the following sections.

### 4.1.1 Cognitive Processes and Motor Response Involved in Driving

Driving is mostly considered a perceptual-motor task, where the requirement for the driver is to manipulate car controls so as to track various changes on their visual environment (Groeger, 2000). Although it is undeniable that driving does involve a considerable amount of motor activity coordinated with visual monitoring, the driving task is more complex than this. The way in which we respond, or are allowed to respond imposes constraints on how we perform the task and on the task we perform (Groeger, 2000).

Most of the time, whilst driving, drivers are not simply looking ahead or around, or accelerating or braking, or steering right or left, but performing each of these actions concurrently, as part of some larger task such as, for example, when following another vehicle or turning at a corner (Groeger, 2000). The driving task depends on an integration of various cognitive and motor processes and Groeger (2000) proposes a framework for modelling driver behaviour (see Figure 4.1) by combining these four processes.

1. A process that detects change which implies some discontinuity in active goals.
2. A process that evaluates this threat.
3. A process to select and construct an appropriate action.
4. A process to modify the actual activity to implement the action

![Diagram of 4 cognitive processes in driving](Figure 4.1: Four cognitive processes involved in a driving behaviour (Groeger, 2000))

It must be noted that different factors can influence these processes. Implied interruption of goals depends, for instance, on behavioural standards, readiness to respond, scene evaluation and spatial judgement. Appraisals of future interruption depend on behavioural responsibility, confidence, extroversion, expectations of self and others and stress (Groeger, 2000).

Action planning is the result of general intelligence, reaction speed and selection. Finally, implementation is related to motor control and coordination (particularly eye-foot and eye-hand). Such structure has been shown to predict actual driving behaviour accurately (Groeger, 2000). This framework highlights the relationship between driving objectives, personality traits and driving behaviour and hence, helps in predicting driver performance. In the case of hazardous driving, the process that anticipates (i.e. action planning and implementation) is impaired. This results in the impairment of all other processes including the implementation process, which is of concern in terms of road safety in case of emergency situations. Importantly, these processes are influenced by personality traits - and experience- which highlights the necessity to model driving differently for multiple groups (i.e. experienced and novice) of drivers.

### 4.1.2 Highly Competent Driving

Competent driving is defined in this thesis as driving behaviour that is characterised by the ability to apply the knowledge, skills and attitude to various driving systems
to achieve a safe journey. This implies that the driver is able to perceive hazards and react appropriately. Normal driving behaviour has been studied largely from a cognitive psychological point of view. It has resulted in the development of numerous, complementary theories which tend to give a comprehensive understanding of a normal driving behaviour. Such theories focus on the cognitive processes involved during the driving task as well as the way drivers cope with the risk associated with the driving task (Groeger, 2000). Indeed preservation of one’s own safety is of concern to drivers but it is not their primary goal whilst driving. The driving behaviour is mainly impacted by concrete goals such as reaching the destination, minimising travel time and avoiding obstacles rather than abstract principles such as safety (Groeger, 2000). Fuller (2005) made a similar observation and states that the risk of collision is generally not relevant in the decision-making loop during driving, as opposed to the feedback regarding the difficulty of the driving task. The main theories are briefly developed in the following paragraphs.

According to the risk homeostasis theory, drivers reach an accepted level of risk which they actively target through weighing up the costs and benefits of alternative actions (Wilde, 2001). This is included in the theory that states, driving is a self-paced task and the driving task demand is fundamentally under the control of the driver through speed selection (Fuller, 2005). This explains why the main factor used by drivers to reach their acceptable risk while driving is speed. The targeted level of risk is also influenced by motivation. This justifies why young drivers are more likely to speed, overtake more and adopt shorter headways and are over-represented in crashes (Jonah, 1997). Next, driver behaviour is determined by the maintenance of safety margins. Safe margins are learned through experience and driving usually becomes a habitual activity which is based largely on automated control of safety margins (Summala, 1988). This provides the ability to highlight the difference between novice and expert drivers because expert drivers use larger safety margins (anticipatory behaviour) which provide opportunities to avoid or correct errors while novice drivers have a reduced ability to understand the road and nevertheless drive in a reactive mode (Brown, 1990). Differences between novice and expert drivers might be detected in such measures.
Figure 4.2 above highlights the difference in terms of competency between novice and experienced drivers’ driving performances. This competency has been identified through existing and previous research (Wallis and Horswill, 2007; Isler et al., 2009; Fridulv and Torkel, 2006). This competency has been further underscored by driver trainers (NDTA 2009; Haynes, 2010 and McDonald, 2010).

Inexperienced driving is defined as the driving performance of a driver that is incapable of competent driving as defined in section 4.1. This mainly includes driving behaviours where hazards are not perceived or perceived too late to react appropriately. Most traffic crashes may be attributed to driver inexperience as a consequence of poor anticipation of hazards and risky attitudes towards dangerous driving practices, such as speeding and not wearing a seat belt (Gulliver and Begg, 2007). These riskier attitudes may be the result of a general overconfidence that young people have with regard to their driving ability and an overestimation of their ability to recover from error if some error does occurs (Gulliver and Begg, 2007).

There is a consensus on the effects of driver inexperience on road safety hazard however no valid framework for a complete evaluation of driving performance is currently available. The effects of these inexperience factors on the undertaking of driving manoeuvres can be monitored and measured empirically using in-vehicle sensors and later analysed for feedback. However, there is no comprehensive model developed for assessing less/highly competent driving. At this stage, the problem is
to identify what makes a driver attempt of manoeuvres less/highly competent. In this thesis, expert drivers’ (i.e. driver trainers) assessments and their driving performance are considered as highly competent. Driving behaviour that diverges from the high competence driving model is considered as low competence driving (gradual variation from high to low competence level). Furthermore, driver trainers’ input on multiple driving scenarios helps facilitate the fine tuning of the low/high competence model.

4.1.3 Uncertainty in Driving Behaviour

Currently, the assessment of drivers is subjective and imprecise (i.e. switching an indicator on 40 metres before a turn is considered to be a high competence driving level, but a distance of 39 meters will not be considered as low competence), which introduces inevitable uncertainty in assessments. Humans do not have the capability to be precise or certain in their perception and evaluation of information for many daily tasks, which involve making decisions in an environment of imprecision and uncertainty (e.g. driving a vehicle or adjusting the hot water in a shower).

Regarding the causes of uncertainty, Klir and Wierman state (cited in Mendel, 2001):
Uncertainty involved in any problem-solving situation is a result of some information deficiency. Information (pertaining to the model within which the situation is conceptualized) may be incomplete, fragmentary, not fully reliable, vague, contradictory, or deficient in some other way. In general, these various information deficiencies may result in different types of uncertainty.

Regarding the nature of uncertainty, Klir and Wierman state (cited in Mendel, 2001):
Three types of uncertainty are now recognized – fuzziness (or vagueness), which results from the imprecise boundaries of fuzzy sets; nonspecificity (or imprecision), which is connected with sizes (cardinalities) of relevant sets of alternatives; and strife (or discord), which expresses conflicts among the various sets of alternatives.

Another source about uncertainty is H.R. Berenji (1988), who states, in agreement with Klir and Wierman, that "uncertainty stems from lack of complete information." The author also states, "Uncertainty may also reflect incompleteness, imprecision, missing information, or randomness in data and a process."
In this thesis, the expert’s knowledge (i.e. driver trainers) is utilised in assessing driver performance and is further used to automate this assessment. This is an issue for current research because driver trainers cannot completely and objectively assess the drivers’ performance for a scenario in an intricate manner. This is mainly due to the large number of data available during driving along with subjective uncertainty. This research has the ability to comprehensively monitor the driving scenario, handle uncertainty and assess driving performance using Advanced Driver Assistance System (ADAS) by identifying the driving differences between novice and experienced drivers. Along with this, cross-checking the identified difference with expert’s knowledge further enhances the credibility of the detected differences between novice and experienced drivers.

4.2 Driver Performance Assessment

Several driver models exist in literature and from a theoretical perspective, the major goal of a model is to describe in detail a process or a system in all its different features. A good model may be limited to an abstract or a conceptual representation of a system, but is able to capture the essence of the fundamental phenomena and behaviours. A more formal definition by Michel et. al. (2009) is:

*A model is essentially a theoretical account of a process or a system based on a number of hypotheses, conservation principles, and simplifying assumptions, which can take the form of analytical functions or differential equations or lexicographic expressions.*

From a historical and theoretical point of view, it is possible to identify different modelling approaches in this field of research during the last decades. They are:-

- The task analysis method providing descriptive models of the tasks and/or the sub-tasks required for driving a car (e.g. Mc Knight and Adams, 1970).
- The Control Theory approach based on the Wiener’s Cybernetics paradigm and primarily focused on the driving performance simulation through mathematical functions of regulation (e.g. Mc. Ruer et al, 1977; Boer and al, 1999).
- The motivational models that are centred on risk assessment (e.g Risk Threshold Model of Naatanen and Summala; 1976, Wilde’s Risk Homeostatis Model 1982, or Fuller’s Threat Avoidance Model, 1984).
The Human Information Processing models specifically focused on cognitive processes and decision making rules modelling (e.g. Michon, 1985; Van der Molen and Botticher, 1988).

These models are mainly theoretical models, in contrast, models developed during the last two decades which aim to provide computational models able to be compared through numerical simulations on a computer. These new approaches can be classified into three categories, (1) reliability assessment, (2) models for simulation of the driver and (3) models for analysis of the driving activity. Briefly, reliability approaches are naturally focused on the probabilities of occurrences of behaviours, decision making or crash risks, without necessary explaining the reason why these effects will occur. The reliability models are dedicated to performance predictions and/or risk calculation. This human reliability model consists of three major functions: (1) on-line performance monitoring; (2) real-time performance forecasting; and (3) performance reliability assessment The models for simulation are virtual models of the human driver which is able to drive a virtual car in virtual environments. The last driving modelling approach, model for analysis, aims to dynamically analyse driving performances implemented by human drivers, from an external observer point of view. This model for analysis can provide on-line or off-line diagnosis concerning the driver status (e.g. level of distraction, drowsiness).

The current research involves differentiating the performance of highly competent drivers from the less competent drivers. Criteria were defined to enable numerical modelling of driving performance as presented in the following section.

4.2.1 Criteria for Performance Assessment

The criteria/model to measure low or high competent driving for driving manoeuvres should include:

- Real time assessment of the driving tasks.
- Allowing uncertainties and imprecision handling. This allows identifying less and highly competent behaviour
- Easily adaptable to change in assessments based on expert’s knowledge.
- Allowing accurate modelling of human knowledge representation.
• Flexibility to add new assessment modules with ease.
• Successful application in domains other than road safety.

4.3 Statistical Modelling of Driving Behaviour

In this thesis, statistical models will be used, since these models are dedicated to performance evaluation and/or a risk assessment in relation to a driving task in a given condition. Consequently, these models can be based on mathematical functions and/or on computational black box(es), whose inputs correspond to the traffic variables and expected predictions (in terms of event occurrence, expected driving performance or level of competence). The models presented for high or low competency assessment of a driving manoeuvre are Hidden Markov Model (HMM), Neural Networks, Generalised Linear Models (GLMs) and fuzzy logic.

4.3.1 Hidden Markov Model (HMM)

Uncertainty can be modelled using Bayesian modelling, particularly dynamic Bayesian networks relevant to modelling sequences of variables, which are often time series. Amongst such networks Hidden Markov Models are the simplest (Russell and Norvig, 2003). Nevertheless, such models have been shown to be effective in many real life applications such as speech recognition (Rabiner, 1989). They have also been successfully applied to model driving behaviour, more precisely for manoeuvre recognition (Gerdes, 2006).

Hidden Markov Model (HMM) is a discrete stochastic process used to model sequence of $T$ observations data (at time $t = 1, 2, \ldots, T$) which are consequences of an unobserved (hidden) variable (Rabiner, 1989). The unobserved variable is the hidden state noted $Q_t$ at time $t$. $Q_t$ is a random variable that can be discrete or continuous, scalar or vector-valued. This variable is the cause of other random variables noted $X_t$ at time $t$, random variables that can be discrete or continuous, scalar or vector-valued. In the case of a HMM, these variables have to follow conditional independence properties for each time $t$ (Bilmes, 2006) summarised in Figure 4.3.
As mentioned in the previous chapters, to measure the safety of driving manoeuvres information has to be comprehensively collected from DVE and then analysed. As applied to this research, the approach consists of inferring the safety of the manoeuvre performed (the hidden state sequence $Q_t$, models one particular manoeuvre) by monitoring the driver and car behaviour as well as the driving environment (observable variables). Different HMMs can be fitted/trained to suit different levels of safety, the difference being in the range of values of observed variables as well as dynamics of changes from one state to the other during the manoeuvre. Afterwards, each manoeuvre can be analysed and it is possible to identify the most probable HMM (high or low competence level) that best describes the observed data. Efficient algorithms exist that perform this learning and inference for Hidden Markov Models (Rabiner, 1989).

Such models can be used in real time once they are trained, shown by their ability to be used for manoeuvre recognition. These models are able to describe discrete variables and hence observable variables can be labelled as high, medium and low competency level. Nevertheless the change from one category to the next is crisp and not gradual. Another advantage is that they are flexible since it is possible to create a new set of assessment by adding the training of new HMMs using the new observable variables of interest.

An issue with HMMs is that it is not obvious to implement field knowledge once the model is trained. The other limitation is that there are a number of ways to drive safely or unsafely, therefore many HMMs will have to be trained (i.e. increased complexity), particularly if trying to obtain a finer scale of high/low competence level. Any high or low competency driving that was not identified prior to the modelling will not be detected. Table 4.1 summarises the review of criteria identified.
for measuring less or highly competent undertaking of a driving manoeuvre using Hidden Markov Models.

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Review</th>
</tr>
</thead>
<tbody>
<tr>
<td>Real time</td>
<td>■</td>
</tr>
<tr>
<td>Easily adaptable to change in assessments based on expert's knowledge</td>
<td>x</td>
</tr>
<tr>
<td>Allows data uncertainty</td>
<td>■</td>
</tr>
<tr>
<td>Allows accurate modelling of human knowledge</td>
<td>x</td>
</tr>
<tr>
<td>Flexibility to add new assessments</td>
<td></td>
</tr>
</tbody>
</table>

Table 4.2 : Hidden Markov Model (HMM)

4.3.2 Neural Networks

Neural Networks (NN) (also known as Artificial Neural Networks ANN) is a mathematical model that tries to simulate the structure and/or functional aspects of biological neural networks. Unlike traditional computer systems, neural networks are capable of learning how to classify and associate input and output patterns (Lippmann, 1987). This capability alone makes neural networks a suitable approach for solving complex problems such as estimating current travel times from traffic flow patterns received from several sources, speech recognition, image recognition and pattern recognition. Neural networks are composed of a network of simple processing elements called neurons, which can exhibit complex global behaviour, determined by the connections between the processing elements and elements parameters. An elementary neuron computes an output from the inputs as follows; first each input $a_j$ is weighted appropriately with $w_{j,i}$, then the sum of the weighted inputs forms the input to a transfer function which provides the output $a_i$. A single neuron is described in Figure 4.4 below.

![Diagram of a neuron](image)

Figure 4.4: A simple mathematical model for a neuron. The unit’s output activation is $a_i = g(\sum_{j=0}^{n} W_{j,i} a_j)$, where $a_j$ is the output activation of unit $j$ and $W_{j,i}$ is the weight on the link from unit $j$ to this unit. $g$ is the activation function.
Neural Networks are a combination of multiple neurons in multiple layers. Figure 4.5 presents a sample model for multilayer feed-forward network. There are two main categories of NN structures (feed-forward network and recurrent network). A feed-forward network is a function of only its current inputs, while the recurrent networks feed their output back into its own inputs. Feed-forward networks are usually structured in layers. Each neuron receives inputs from the immediate preceding layer. Neural networks can have a single layer or multiple layers (Lippmann, 1987) and adding a number of layers help to model complex problems.

![Multilayer feed forward network architecture for neural network with three layers and n inputs X and m outputs Y (Lippmann, 1987)]

Such a system tries to simulate the structure and/or functional aspects of biological neural networks. Neural Networks are therefore non-linear data modelling tools that can be used to model complex relationships between inputs and outputs or to find patterns in data. In most cases NN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase (Caudill and Butler, 1992). This capability alone makes neural networks a suitable, widely used approach for solving complex problems, such as estimating patterns from data received from several sources.

The utility of artificial neural network models lies in the fact that they can be used to infer relationships between variables from observations (Caudill and Butler, 1992). This is of particular interest for applications where the complexity of the data or task makes the definition of this relationship theoretically intractable. Such models can be used for many applications, including predictions in real-time and modelling complex evolutions of the output without any prior assumptions. This explains why they have been largely used in wide areas of research, particularly since they provide
accurate results and can often adapt to unseen situations. For instance, they have been used in process control, pattern recognition (e.g. object recognition) and sequence recognition.

NNs can be used in this research to assess the competency of a manoeuvre. Training such models require performance assessment of the manoeuvre performed by driver trainers. A driver trainer assesses the different risk indicators (i.e. distance from the turn, gaze span etc). These calculated data are used as outputs of the neural network. Data collected during the driving are used as inputs for the neural network. The neural network can then be trained to highlight the patterns between driver, vehicle and environment data and low competency indicators.

Such modelling can be used in real time and implemented in a way that provides a discrete output, i.e. a discrete competency assessment such as high, medium and low. Also, to implement new rules, it is necessary to train the whole model again. This reduces the flexibility in adding new assessment modules; additionally it can be time consuming. Table 4.2 summarises the review of criteria identified for measuring less or highly competent undertaking of a driving manoeuvre using Neural Networks.

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Review</th>
</tr>
</thead>
<tbody>
<tr>
<td>Real time</td>
<td>✔</td>
</tr>
<tr>
<td>Easily adaptable to change in assessments based on expert's knowledge</td>
<td>✗</td>
</tr>
<tr>
<td>Allows data uncertainty</td>
<td>✔</td>
</tr>
<tr>
<td>Allows accurate modelling of human knowledge</td>
<td>✗</td>
</tr>
<tr>
<td>Flexibility to add new assessments</td>
<td>✔</td>
</tr>
</tbody>
</table>

Table 4.3: Neural Networks (NN)

4.3.3 Generalised Linear Model (GLM)

Generalised Linear Models (GLMs) were formulated by Nelder and Wedderburn (1972) as a way of unifying various statistical models, including linear regression, logistic regression and Poisson regression under one framework. This allows the development of a general algorithm for maximum likelihood estimation in all these models. Such models are a flexible generalisation of ordinary least squares
regression (linear regression) allowing the linear model to be related to response variable via a link function (Nelder and Wedderburn, 1972).

GLMs are a generalisation of ordinary least squares regression which relates to the distribution function of the measured variable of an experiment \( Y \) to the explanatory variables of the experiment \( X \) (through the linear predictor \( \eta \)) through a link function \( g \). In a GLM, the samples are assumed to be independent and identically distributed (i.i.d.) and \( Y \) is assumed to have a distribution function \( f \) (parameterised by \( \theta \) and \( \tau \)) in the exponential family (Nelder and Wedderburn, 1972).

\[
f_Y(y; \theta, \tau) = \exp \left( \frac{a(y)b(\theta) + c(\theta)}{b(\tau)} + d(y, \tau) \right)
\]

where \( \tau \) is the dispersion parameter, \( \theta \) a parameter linked to the mean of the distribution, \( a, b, c, d \) and \( h \) are known functions. The mean of \( Y \) depends on the linear predictor as follows (Nelder and Wedderburn, 1972).

\[
\begin{align*}
E[Y] &= g^{-1}(\eta) \\
\eta &= \beta X = \sum_i \beta_i X_i
\end{align*}
\]

where \( E[Y] \) is the expected value of \( Y \) and \( \beta \) a unknown parameter to be estimated.

The generalised linear model can be seen as an extension of linear multiple regression for a single dependent variable. The general purpose of multiple regression (the term was first used by Pearson, 1908) is to quantify and predict the relationship between several independent or predictor variables and a dependent or criterion variable (Dobson, 2001).

Such models can be applied to this research in a similar way as Neural Networks. A driver trainer is required to assess the different performance indicators. These assessments are used as outputs of GLMs. Such outputs are the result of a linear combination of the different measures obtained from the driver, the vehicle and the environment (inputs or predictors). Such linear combination can result in complex trend modelling of the performance indicator through polynomial combination of predictors.

As the previous models presented, GLMs can be used in real-time. These models have been used for many applications and are able to provide information on significant predictors (i.e. pattern recognition, speech recognition) (Rabiner, 1989).
Another advantage is that it is possible to add new assessment modules through the training of new GLMs for the added performance indicators only.

The first issue with these models is that they cannot take into account inter-individual variability. Such limitation can be overcome by using Generalised Linear Mixed Models (GLMMs). GLMMs extend GLMs through the inclusion of random effects in the linear predictor. These random effects provide a probability model that explains the correlations of data collected relating to one particular driver. Another issue is that it is not possible to utilise expert knowledge to tune the obtained model once the model is trained. Table 4.3 shows the review of criteria identified for measuring less or highly competent undertaking of a driving manoeuvre using Generalized Linear Model (GLM).

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Review</th>
</tr>
</thead>
<tbody>
<tr>
<td>Real time</td>
<td>✔</td>
</tr>
<tr>
<td>Easily adaptable to change in assessments based on expert's knowledge</td>
<td>✗</td>
</tr>
<tr>
<td>Allows data uncertainty</td>
<td>✔</td>
</tr>
<tr>
<td>Allows accurate modelling of human knowledge</td>
<td>✗</td>
</tr>
<tr>
<td>Flexibility to add new assessments</td>
<td>✔</td>
</tr>
</tbody>
</table>

* ✔ accommodated
* ✗ not accommodated

Table 4.4: Generalised Linear Model (GLM)

### 4.3.4 Fuzzy Logic

The concept of fuzzy sets was first introduced by L. A. Zadeh in 1965. Since its introduction, it has been used in many areas related to human perception such as the analysis of workload and risk in the workplace. Fuzzy sets, where a more flexible sense of membership is possible, are classes with un-sharp and vague boundaries. Fuzzy set theory is a branch of a set theory that is useful for the representation of imprecise knowledge of the type which is prevalent in human concept formation and reasoning because fuzzy theory can represent a type of uncertainty due to vagueness or fuzziness (Yen and Langari, 1998; Tsoukalas and Uhrig, 1996; Yager, 1986).

Probability measures “likelihood of occurrence” which is related to the following question, “How often or frequently does it happen?” While a fuzzy set measures
“the degree of certainty” and is related to following question, “How sure are you that it happens?”. Zadeh states that this limitation is due to the lack of probability theory to operate on human perception-based information, which is commonly described through a natural language (Zadeh, 1996).

Fuzzy logic is used for solving complex problems in a more natural way by approximate reasoning. Human experts’ performance is heavily dependent on domain knowledge, common sense reasoning and learning. Fuzzy logic is one of the methodologies for incorporating these characteristics into systems, allowing complex problems to be solved at the human expert level (Palacharla and Nelson, 1999). Fuzzy logic is primarily concerned with knowledge representation (both precise and imprecise). The concept of fuzzy sets has been developed for various types of analysis methods such as fuzzy numbers, fuzzy relations and fuzzy inference systems. Recently, these fuzzy sets have been combined with statistical methods and other intelligent methods, for example, neural networks and genetic algorithms. The basic fuzzy set method consists of three components; fuzzification, fuzzy operation and defuzzification (Tsoukalas and Uhrig, 1996).

Fuzzy logic in the past has been applied in transportation engineering for traffic control and crash prediction (Robertson, 1979; Favilla et. al., 1993). Fuzzy sets and fuzzy logic are used successfully in many real world applications such as automatism, robotic, informatics, decision making problems, medicine and pattern recognition, as they enable the representation of imprecise knowledge and concepts (Zadeh, 1996). They can be implemented in real time and with an appropriate structure, can be used for effective modelling of competency levels. As such, fuzzy modelling is quite powerful in modelling complex real world problems due to its flexibility.

Table 4.4 shows a review of criteria identified for measuring less or highly competent undertaking of a driving manoeuvre using fuzzy logic.
CHAPTER 4. PERFORMANCE ASSESSMENT

4.4 Comparison of Approaches

The ability of different models to follow the criteria required for this study, as mentioned in Section 4.2 (Criteria for Performance Assessment), is summarised in Table 4.5 below. Amongst the different model reviewed, only fuzzy logic appears to accommodate all the criteria identified for an effective assessment of driver performance while manoeuvring. Fuzzy logic for performance assessment has been selected for implementation in this thesis and its validation has been made by analysing the results retrieved after conducting the test drives compared with the expert’s (i.e. driver trainers) assessment.

Table 4.5: Fuzzy Logic

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Review</th>
</tr>
</thead>
<tbody>
<tr>
<td>Real time</td>
<td>![accommodated]</td>
</tr>
<tr>
<td>Easily adaptable to change in assessments based on expert’s knowledge</td>
<td>![accommodated]</td>
</tr>
<tr>
<td>Allows data uncertainty</td>
<td>![accommodated]</td>
</tr>
<tr>
<td>Allows accurate modelling of human knowledge</td>
<td>![accommodated]</td>
</tr>
<tr>
<td>Flexibility to add new assessments</td>
<td>![not accommodated]</td>
</tr>
</tbody>
</table>

Table 4.5: Fuzzy Logic
### Approach

<table>
<thead>
<tr>
<th>Approach</th>
<th>Real Time</th>
<th>Handle Uncertainty</th>
<th>Modelling of human knowledge</th>
<th>Adaptable to assessment change</th>
<th>Addition of new assessments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hidden Markov Model</td>
<td>■</td>
<td>■</td>
<td>●</td>
<td>●</td>
<td>■</td>
</tr>
<tr>
<td>Neural Networks</td>
<td>■</td>
<td>■</td>
<td>●</td>
<td>●</td>
<td>■</td>
</tr>
<tr>
<td>Generalised Linear model</td>
<td>■</td>
<td>■</td>
<td>●</td>
<td>●</td>
<td>■</td>
</tr>
<tr>
<td>Fuzzy Logic</td>
<td>■</td>
<td>■</td>
<td>■</td>
<td>■</td>
<td>■</td>
</tr>
</tbody>
</table>

- ■ Accommodated
- ● not accommodated

Table 4.6: Review table for the potential approaches and criteria
4.5 Basics of Fuzzy Set and Fuzzy Logic

Set theory, the basis of modern computing, has often been criticised as an extreme oversimplification of reality (Palaharla, 1995). Regular set theory lacks the ability to handle uncertainty, a situation commonly encountered in the real world. To overcome this difficulty, Zadeh introduced fuzzy sets (Zadeh, 1965). A fuzzy set is an extension of a regular set in which each element has a degree of membership associated with it, which can be any value between 0 and 1. An element, whose degree of membership in a set is 0, is not present in the set whereas an element whose degree of membership is 1 belongs one hundred percent to the set. An element with a degree of membership in a set of 0.8 belongs eighty percent to that set and so on. An element can belong to more than one set with varying degrees of membership (Palacharla and Nelson, 1999). This provides a powerful scheme for the representation of uncertainty. Thus, continuous or fuzzy logic does encompass conventional or binary logic as a special case but it extends beyond that as well.

The continuous or fuzzy logic differs from binary logic in that the degree of membership varies from 0 to 1. The membership function in binary logic jumps suddenly from 0 to 1 at a crisp point, whereas the membership function in fuzzy logic can vary from 0 to 1 and from 1 to 0 smoothly. Also, the membership functions for various fuzzy sets can overlap. A main advantage to applying fuzzy logic for solving real world problems is its ability to capture non-linear relationships between inputs and outputs without much oversimplification (Palaharla, 1995).

4.5.1 Membership Functions and Linguistic Variables

Membership function is the most important element of the fuzzy approach, as it allows the fuzzy approach to evaluate uncertainty and ambiguity. The role of the fuzzy membership function is to represent subjective human perception using the concept of a fuzzy set (Lee and Donnel, 2007). As mentioned above, in a classical set or crisp set, the objects in a set are called elements or members of the set. A characteristic function or membership function $\mu_A(x)$ is defined for any element (x) in the universe U having a crisp value of 1 or 0.
For every \( x \in U \),

\[
\mu_A(x) = \begin{cases} 
1 & \text{for } x \in A, \\
0 & \text{for } x \notin A. 
\end{cases} 
\]  

(1)

For the classical set or crisp set, membership functions take a value of 1 or 0, for fuzzy sets, the membership function can take values in the interval \([0, 1]\). The range between 0 and 1 is referred to as the degree of membership (Bojadziev, 1995). A fuzzy set is characterised by several membership functions, \( \mu_A \), defined as functions from the well-defined universe \( U \), into a unit interval, 0-1.

\[
\mu_A : U \to [0,1] 
\]  

(2)

This membership function represents the degree of subjective notions of a vague class with an infinite set of values between 0 and 1. The task for determining the membership functions is a very critical step in the fuzzy analysis procedure. Numerous types of fuzzy membership functions include triangles, trapezoids, bell-shape curves, S-shape curves, Gaussian and sigmoid functions (Lee, 2006). In fuzzy logic systems, neighbouring membership functions overlap to indicate that a value may belong to different sets at the same time, with different degrees of membership.

In order to calculate the membership degree for a particular fuzzy membership function, the following formula are used:
Linguistic variables are used in conjunction with fuzzy membership functions for fuzzy analysis. While variables in mathematics usually take numerical values, in fuzzy logic applications, the non-numeric linguistic variables are often used to facilitate the expression of rules and facts (Zadeh, 1996). For example, to answer the question "What is it like outside?", one might say "It is warm outside". Experience has shown that if it is "warm" and the time is mid-day, a jacket is unnecessary but if it is warm and early evening, it would be wise to take a jacket along (the day will change from warm to cool). The linguistic variable such as "warm" common in everyday speech, convey information about our environment or an object under observation. The word ‘warm’ could be 31 degrees, but if it is 33 degrees, it could still be considered as both ‘warm’ and ‘hot’. The fuzzy membership functions combined with these linguistic variables will return a degree of membership for both ‘warm’ and ‘hot’ functions (i.e. 33 degrees could be 0.8 warm and 0.2 hot). This process is also known as fuzzification of the inputs. This process of fuzzification combined with rules is the central processing unit of the fuzzy logic manipulations. Figure 4.7 below presents an example of a
The antecedent describes a condition and the consequent describes a conclusion that can be drawn when the condition holds. For example, if the weather outside is ‘warm’ and time is ‘early evening’, then suggestion will be ‘take the jacket’.

Basically, fuzzy expert system is a set of fuzzy if-then rules that convert inputs to outputs (Kosko, 1993). Each input to the fuzzy expert system fires all the rules to some degree as in an associative memory. The closer the input matches with the if-part of a fuzzy rule, the more the then-part fires. The fuzzy expert system adds up all these then-part fuzzy sets and takes their weighted average or centroid value.
This centroid is the output of the fuzzy expert system. The entire manipulation of input using fuzzy logic is described in Figure 4.8 which is presented below.

**Figure 4.8: Structure of a fuzzy logic based inference system (Lee Donnel, 2007)**

- **To fuzzify inputs**
  The first step is to take the inputs and determine the degree to which they belong to each of the appropriate fuzzy sets through membership functions (MatLAB guide).

- **To apply fuzzy operator**
  If the antecedent of a given rule has more than one part, the fuzzy operator is applied to obtain one number that represents the result of the antecedent for that rule using; and/or complement, product or multiplying rule.

- **To aggregate all output**
  Since decisions are based on the testing of all rules in a fuzzy inference system, the rules must be combined in some manner to make a decision. For example:
  A) If the weather is ‘warm’ and time is ‘evening’, then suggestion is to ‘take the jacket’.
  B) If the weather is ‘warm’ and time is ‘morning’, then suggestion is to ‘leave the jacket’.

- **To defuzzify**
  The result is described with a fuzzy value and must then be translated into a single natural number (i.e. crisp value).
CHAPTER 4. PERFORMANCE ASSESSMENT

Using fuzzy logic to assess competency based on expert knowledge is feasible. This research describes the use of fuzzy set theory for competency evaluation and analysis of the driving manoeuvres. This rule-based behaviour is driven by a large set of rules which may be written as conditional statements (e.g. if vehicle speed is 50km/h and traffic light has just turned red, then must slow down vehicle and prepare to stop). By using expert’s knowledge to make these set of rules for highly competent driver manoeuvring, less competent undertaking of driving manoeuvres can be segregated from the driving scenario and addressed accordingly. The safety judgment models are made up with the help of fuzzy set theory. Detailed explanation of the use of fuzzy logic to assess driving manoeuvres is presented in Chapter 6.

4.6 Summary

This chapter highlights the gap in assessing different competence levels in driver performance. Driving is a task that can be potentially lethal to drivers, passengers and pedestrians alike, although most drivers hold expectations that such events will not occur. The assessment of critical parameters (i.e. scanning the road and evaluating distances and speeds of surrounding vehicles/obstacle with respect to their vehicle) enable drivers to manoeuvre through the roads within low or high competency levels. These assessments can differentiate a novice driver from an experienced driver. By measuring the variables involved in driver manoeuvring, a model can be identified to measure the competency level achieved within a certain manoeuvre.

This chapter explains the driving behaviour from a psychological perspective and further explains the cognitive processes involved whilst driving. It further elaborates on competency during driving and defines a low and high competency model for this thesis. This chapter also presented the mathematical models that can be used to assess drivers’ manoeuvring in real time using expert knowledge. It identified fuzzy logic as the approach that satisfied all criteria laid out to effectively assess driving performance which was presented in section 4.2.

Along with Chapter 2 and 3, this chapter has developed a theoretical base for assessment of competency involved in undertaking different driving manoeuvres.
The following chapters will provide a validation and prototype of these theoretical foundations. The statistical model identified (i.e. fuzzy logic) in this chapter will be used to assess driving performance. Furthermore to test the framework, a study is conducted to identify empirically, the differences in novice and experienced drivers’ undertaking of manoeuvres. This is followed by modelling the differences between the two groups using fuzzy logic.
Automobiles are highly regulated products for multiple reasons which include safety, energy conservation and environmental protection. All these features (i.e. safety, energy and environmental protection) have to be standardised for harmonisation of vehicle standards. The previous chapters paved way for the presentation of such a safety system that will enable the automated assessment of driving manoeuvres. Driving is fundamentally a self paced activity because by and large it is the driver who determines the speed and direction of the vehicle and also the rate of information flow, the available time for hazard detection, decision making and responding and the likelihood of getting into a conflict with other road users (Fuller 2000). Young drivers’ lack of driving competency contributes to crashes (Fuller 2000). Driver competencies have been mainly assessed subjectively by driver trainers and to our knowledge there is no automated system that can objectively assess competencies. A system that can use existing Advanced Driving Assistance Systems (ADAS) to extensively assess driving competencies is needed. This chapter presents an Intelligent Driver Training System (IDTS) that provides a computational model for competency assessment in relation to the driving tasks performed during a particular manoeuvre. With the help of this driver training system, the research questions identified in Chapter 1 will be addressed. The questions are:
What are the differences between novice and experienced drivers when they attempt certain driving manoeuvres?

Can these differences be evaluated using expert knowledge and assessed as of high or low competence levels?

Can an interactive interface be designed that presents the driving task’s assessments in an effective manner?

This chapter related to intelligent driver training system (IDTS), will discuss the concept and a high level design of such a system. The current chapter also illustrates a detailed component diagram for this training system. It presents the synchronization of multiple sensor inputs and their processing in detail. Section 5.2 explains the architecture of Intelligent Driver Training System (IDTS) and examines the modules of this system (i.e. data registration, manoeuvre identification and assessment/potential feedback). The working model of IDTS, introduced in section 5.2, presents the algorithms for gaze/fixation mapping, vehicle trajectory calculation and multiple manoeuvre recognition/segmentation in detail. Finally, section 5.3 includes a summary of the entire chapter.

5.1 Intelligent Driver Training System (IDTS)

Many hours of practical experience under realistic conditions is necessary for new drivers to reach a point where they are able to routinely and smoothly handle all but the most untypical driving situations. Most novices learn simple manoeuvres such as starting, stopping, reversing and turning a vehicle within a few hours and become fairly good at them in a matter of days. Catchpole et al. (1998) analysed casualty crash data and found drivers aged 18 to 20 years were more likely to be over represented in single vehicle “off path” crashes (i.e. loss of vehicle control) than those aged 21 to 25 years.

A great deal of understanding and ability of driving situations is needed on part of drivers to drive competently and safely. For example, drivers need to be able to routinely identify and react to a vast array of potentially hazardous situations, manoeuvre the vehicle in complex traffic situations, avoid being distracted at critical times and deal with passengers, to name only a few. Each trip involves unique
situations that demand near-constant attention and instantaneous decisions (Foss, 2009).

In the previous chapters, it has been noted that driver’s perception and driver’s learning of driving hazards remains a key factor impacting road safety (Aufrere et al., 2003). To develop useful measures in tackling road safety issues, a complete and integrated framework needs to be developed which will include and examine all the parameters that influence driving (i.e. cues related to road, vehicle and driver).

Figure 5.1 presents a high level dataflow diagram for such a training system. More details about each layer will be presented later. To our knowledge, the Advanced Driver Assistance System (ADAS) has never been comprehensively used in a driver training context to assess driver performance.

The proposed training system addresses this gap by building upon traditional ADAS to deliver a comprehensive assessment of driving manoeuvres. This training or education system extends the outputs from Layer 1 and utilises that information in Layer 2 to determine the driving competencies.

- **Layer 1:** The existing ADAS systems that can be employed in layer 1 include lane detection system, obstacle detection system, vehicle dynamics, driver head and eye movement together with arms and feet positioning as well. These systems usually track and assess individual variables such as either driver or vehicle or environment instead of integrated monitoring.

- **Layer 2:** The core of layer 2 comprises of algorithms and tools that synchronizes the parameters and evaluates them based on a “performance
assessment driving criteria” already designed by professional driver trainers. In layer 2 all the data communicated from the layer 1 is time stamped, synchronised and evaluated.

Figure 5.2 presents a deeper understanding of the block diagram illustrated in Figure 5.1. It shows how the traditional ADAS systems can be used to build an Intelligent Driver Training System (IDTS). It is a detailed component diagram of Figure 5.1 presented above. The major addition is the integration of variables from DVE (driver, vehicle, and environment) and the evaluation criterion that is based on rules by driver trainers, which determines if the manoeuvre performed belonged to high or low competency level. The automation of assessment for the driving manoeuvres based on these rules, from the data acquired through sensors in Layer 1, is a unique feature of IDTS. Though there have been some assessments using traditional assessment systems (e.g. forward collision warning (FCW), electronic stability control (ESC)), that monitor some but not all of the three features involved in driving namely driver, vehicle and environment (DVE). IDTS is able to comprehensively assess data from all three parameters (i.e. DVE) and assess the proficiency based on expert’s knowledge.

The top section (clear) in figure 5.2 describes the evaluation that the intelligent driver training system will perform. This evaluation is made while taking into account the assessment criteria used by driving instructors. This added module acts as an enhancement to the ADAS system (bottom section of Figure 5.2).

Figure 5.2: The intelligent driver training system built upon ADAS (Second level diagram based on figure 5.1)
As previously mentioned, to our knowledge there is no Intelligent Transportation System (ITS) technology currently available to improve driver training. Even though there has been significant research focused on improving driver training practices, a comprehensive solution is yet to be discovered. A system that will be able to assess driving performance will complement the driving instructors by offering objective assessment.

Such a comprehensive driving training system has to integrate data effectively from the following three fields: Driver, Vehicle and Environment (DVE) and assess multiple driving manoeuvres. For convenience, this thesis will go on to consider a limited set of manoeuvres in detail. These are: driving ahead near other road vehicles, left turn on a curve and left at T-junctions, as well as changing lanes, overtaking and stopping. It should be noted that even though IDTS is built upon ADAS, the intelligent driver training system is not an ADAS.

5.2 Architecture of IDTS

To model a complex driving scenario in a comprehensive manner, it is necessary to integrate several sensory data.

Figure 5.3: Top level architecture of IDTS

Figure 5.3 presents the block diagram of the top level architecture of Intelligent Driver Training System (IDTS). All outputs are gathered from multiple sensors (located inside and outside the test vehicle) throughout the driving task and then synchronized followed by recording of all the driving data. By integrating information about the vehicle, driver and environment we are able to formally contextualise, observe and assess a more complete range of driver behaviours. After the data synchronisation, manoeuvres are segmented out as right turn, left turn, lane change and overtake. Each manoeuvre is composed of several individual tasks that are necessary to be performed in a timely manner. This sequence of task completion helps driver trainers to subjectively assess the drivers during execution of different manoeuvres. IDTS further uses expert knowledge in the form of rule based system to evaluate the competency associated with performed manoeuvres. Finally, it uses a
mapping module combined with graphical representation of the driving scenario to provide potential feedback about the driving tasks.

Figure 5.4 below, describes the variables which the driver training system will monitor and evaluate. This is similar to the condition that a driver has to face and judge during driving based on a number of variables (environment, current car dynamics). The driver training system will integrate the information acquired from the DVE and then classify it into manoeuvres. The manoeuvres will then be recognised and analysed using the rules set by the driving instructor. Finally, the performance analysis of these manoeuvres will determine if the driving was of high competence level or not. Our system, called the Intelligent Driver Training System (IDTS) mainly consists of three main modules (i.e. Data Registration Module, Manoeuvre Identification Module and Assessment Module). Details of these modules are provided in sections 5.2.1, 5.2.2 and 5.2.3.

A brief overview of the three modules (i.e. Data Registration Module (DRM) present in Data Registration Layer, Manoeuvre Identification Module (MIM) present in Manoeuvre Identification Layer and Assessment Module present in Assessment Layer) is followed. The DRM is responsible for handling all the data channelled to it through sensors. And MIM manages the identification and characterisation of the manoeuvres. This is an integral layer since it is responsible for converting the synchronised data into information. Finally, the assessment module conducts the performance analysis of individual manoeuvres and presents the visual representation of the driving tasks for possible feedback regarding the driving manoeuvres. The processing layers and the data flow amongst these layers are illustrated in Figure 5.4 below.
Section 5.2.1 will present the architecture of Data Registration Module (DRM) in detail and sections 5.2.2 and 5.2.3 will demonstrate the architectures of MIM and Assessment module respectively.

5.2.1 Data Registration Module

This (Data Registration Module (DRM)) is the first module that interfaces with all connected sensors located inside and outside the test vehicle.

Any device equipped with one or several sensors can be referred to as a sensing platform. In this thesis, the sensing platform is a 2007 Toyota land cruiser (Registration No: 079 KFY) on loan from QFleet to CARRS-Q as an in-kind contribution towards the ARC Linkage project for three years. The term test vehicle will be used consequently to refer to the equipped four wheel drive. The multiple sensors that are present in the test vehicle are presented in Figure 5.5. The details of these sensors are given in ‘recording scenario’.
This section 5.2.1 will present, in detail, all the different sensors and their interface, which are utilised to obtain a comprehensive view of the driving task. It will also present the synchronisation of all these sensors using the recording components in \textit{RTMaps}.

### 5.2.1.1 Synchronization Interface

\textit{RTMaps} (Real Time, Multisensor, Advanced Prototyping Software) is used as a tool to synchronise and record the multiple sensor inputs. \textit{RTMaps} is the software that allows real time multiple data acquisition, data integration and processing, at a high rate. The acquired data can also be stored for future replay. Heterogeneous data such as the speed of the car, steering wheel angle, vehicle positioning is recorded by \textit{RTMaps}. The head and eye movement is also recorded in \textit{RTMaps} using faceLAB. Along with this the input from the road environment is also recorded.

This software records and timestamps data from different devices and sensors at varying frequencies (Figure 5.5 presents \textit{RTMaps} at work). This software is able to synchronise all the data collected so that the experiment can be replayed and analysed later. Figure 5.6 shows the different features of the \textit{RTMaps} product and the way they work together.
Figure 5.6: The RTMaps architecture

5.2.1.2 Recording scenario (In-vehicle sensors)

Figure 5.7 illustrates the location of sensors inside the test vehicle. The sensors are: namely faceLAB (eye tracking system), MobileEye (lane and obstacle detection system), cameras (road images in front), and Vigil System (GPS and vehicle dynamics data logger) to gather data from the driver, environment and vehicle respectively. IBEO Laser scanner (distance from the following vehicle) is placed in the rear of the test vehicle (outside) to measure distance of the following vehicles. RTMaps is used to synchronise data from all the above mentioned sensors with different frequencies.
A detailed description of the sensors that were used to gather data from driver, vehicle and environment are provided below.

A) Lane and Obstacle Detection

The lane and obstacle detection is performed using two off-the-shelf Advanced Driver Assistance System (ADAS) namely Mobile Eye and IBEO laser scanner.

Mobile Eye system is a vision-based ADAS, providing data for applications such as Lane Departure Warning, Forward Collision Warning, Headway Monitoring and Pedestrian Detection. It is a single camera, based safety solution, which is mounted on the windshield of the test vehicle. This system provides data for lane positioning as well as obstacle position with respect to the front of the test vehicle.

In order to retrieve the location of obstacles in the rear of the test vehicle, IBEO laser scanner is used. Figure 5.8 presents the laser scanner which is mounted on the middle of the rear bumper of the test vehicle. Some of the key features of this laser scanner include: detection range of 200 meters, total field of view is greater than 180 degrees and frequency is approximately 25 Hz. In addition, the IBEO LiDAR is able to classify objects as car, trucks, pedestrian, cyclists, along with localising the object detected.
B) Vehicle position and vehicle dynamics

The vehicle position on the road (i.e. GPS coordinates) and vehicle dynamics (i.e. indicator status, brakes, speed and excessive acceleration or deceleration) are retrieved by Vigil Vanguard system. Vigil Vanguard is a highly portable system that can be quickly installed in any vehicle. This system was used in this study to gather data about the vehicle position and dynamics. This visual-based management software program analyses several areas of driving performance. Using GPS, accelerometers and cameras it measures speeds, accelerations, braking, cornering, following distances. The GPS input from this system is used to accurately view the vehicle’s trajectory (Vigil Vanguard).

This system was not initially designed to interface with RTMaps. In-order to manage this issue, the data collected by Vigil Vanguard system was exported using module utilising sockets (in C#). The exported data was then recorded through RTMaps.
Figure 5.9 shows the updated design of the recording module for Vigil Vanguard system. The Vigil system that is connected to the GPS, Mobile Eye (M.E.) and Inertial Sensor (I.S.) transmits data to RTMaps. RTMaps then stores this multiple sensor outputs in its time stamped data files. This time stamped data can then be used to replay the driving scenario and perform post processing on sensor outputs. The author will like to acknowledge the assistance of Vigil Systems Pty. Ltd. and its employees in interfacing the Vigil Vanguard system with RTMaps.

C) Eye Tracking Data

faceLAB™ is a device that can track head and eye movements using two cameras and infrared light sources. This requires calibration to be performed in two stages. First, the position of the cameras, screen and participant have to be set so that the software can have accurate axis to represent the “world” (simulator room), compute head and eye positions and is able to infer where the driver is staring on the screen. This is done once when the simulator room is set.

It has to be noted that two modes of precision are available with faceLAB™; (i) standard mode and (ii) precision mode. The former is more robust towards glare or light disturbances and is adapted to experimentation performed outside. The latter requires stable conditions but provides more accurate values. The precision mode
was used in this study since conditions in the simulator room are controlled. Secondly, a model of the face of each driver has to be created before the first driving session. This part is critical to ensure good eye tracking performance and was performed manually because the automatic mode did not produce satisfactory results. This setting enables faceLAB to detect specific features of the driver’s face (particularly eyes and mouth corners and nostrils) from a picture that is detected during tracking (see Figure 5.10). Hence, head rotation, eye position and eye can be detected for each participant.

faceLAB™ can export the data collected to a disk drive or to the network through TCP/IP protocol. Within RTMaps®, a library was available to extract data from faceLAB™. This library collects data from the network, adds a timestamp and saves the data as a file readable in MATLAB.

![Figure 5.10: Head and Eye calibration and tracking using faceLAB™](image)

### 5.2.1.3 Integration of all Sensors Data

The driving task and data collected from the sensors is synchronised on a dedicated computer running RTMaps. All the sensors were connected to a D-Link 5-Port 10/100/1000 Ethernet switch (DLink) for transferring data using TCP/IP.
In the meantime, sensors were transferring data at different frequencies and all the data from the heterogeneous sensors were time-stamped and stored for future processing. Data obtained from the VigilVanguard system, which is responsible for registering data from GPS, inertial sensor and lane/obstacle position in-front of the vehicle was read using the sockets component in RTMaps. In order to integrate VigilVanguard system with RTMaps, a module was added to output all the data read from the sensors (connected to VigilVanguard) to multiple socket ports.

Along with this, the socket components in RTMaps were responsible for retrieving data from faceLAB™ and the IBEO laser scanner relating to driver eye movement and position of the obstacles behind the test vehicle respectively. The faceLAB™ decoder component provided the liberty to record only head and eye related data required for this research. The camera with a fish eye lens recorded images of the road in-front of the driver. Another camera was attached on the side of the vehicle to record images of the vehicle with respect to the lanes. All the recorded data were stored in RTMaps file format. This recording framework is summarised in the RTMaps diagram presented in Figure 5.11. This diagram shows how different components were interconnected to synchronise the multiple sensors within this experiment.

Figure 5.11: Recording diagram for multiple sensors used in Intelligent Driver Training System (IDTS)
Table 5.1 shows the different components (and their functions) involved in recording the driving data. This driving scenario’s data is later processed and converted into information related to the manoeuvres performed and their associated competency levels.

<table>
<thead>
<tr>
<th>Components</th>
<th>Performed Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>RawSocketReceiver_comf</td>
<td>Retrieves inertial sensor (i.e. acceleration/deceleration) data through sockets</td>
</tr>
<tr>
<td>RawSocketReceiver_gps</td>
<td>Retrieves GPS sensor data through sockets</td>
</tr>
<tr>
<td>RawSocketReceiver_aws</td>
<td>Retrieves lane and obstacle data (i.e. in-front of the vehicle) through sockets</td>
</tr>
<tr>
<td>RawSocketReceiver_FL</td>
<td>Retrieves faceLAB data (i.e. head and eye position) through sockets</td>
</tr>
<tr>
<td>RawSocketReceiver_LIDAR</td>
<td>Retrieves obstacle data (i.e. rear of the vehicle) using IBEO Laser scanner through sockets</td>
</tr>
<tr>
<td>WDM_fishEyeCam_Capture</td>
<td>Retrieves images of the road ahead</td>
</tr>
</tbody>
</table>

Table 5.1: Name and function/purpose of the components involved in recording of the driving data

5.2.1.4 Processing scenario

As already referred, data synchronisation is done with RTMaps®. This involved creating new components to synchronise new sensors. An RTMaps® component is composed of inputs and outputs (their number depends on requirements) which can share/transfer data to other components or external applications through serial/USB ports or the network (TCP/IP, UDP). Once the data from multiple sensors were recorded in RTMaps file format, it has to be converted in-order to be processed with MATLAB. This is addressed by creating new processing components in RTMaps® (using C/C++). Such components have a standardised architecture composed of three functions to obtain outputs from the inputs. The three functions are as follows:

- **Birth()**: initialise variables and buffers. This function is executed once in the first instance.
- **Core()**: this function contains the main part of the code and is executed as a cyclic loop.
- **Death()**: utilised to close everything that was opened by the previous functions.
These functions are coded in C/C++ language and required some adaptation with the specific architecture of RTMaps®. The methodology used to synchronise data in this study is summarised in Figure 5.12. It shows data from multiple sensors being read with RTMaps and later RTMaps is able to generate files that can be processed using MATLAB. Different parts of this synchronisation are detailed in the following sections.

Figure 5.12: Sensor synchronization using RTMaps

Figure 5.13 shows a working example of each component inside RTMaps. It illustrates how each processing component retrieves the recorded data (dashed line) and passes through the multiple stages of the component to generate (solid line) a file readable in MATLAB.

Figure 5.13: RTMaps component’s architecture employed for generating files that are later processed in MATLAB

The recorded data for each sensor (i.e. faceLAB, vigil Systems, IBEO LiDAR, Mobile Eye and cameras) passes through Birth() function for each processing
component and it initialises the buffers and variables that will be used during the program execution. Each component can be initialized to retrieve data belonging to one particular sensor.

The recorded data for each component is then processed in $Core()$ in a cyclic manner. This loop enables each component to convert and store the data into a MATLAB readable file format. Figures 5.14 and 5.15 show the $\text{RTMaps}^\text{®}$ diagrams and the connections of the components involved in processing the $\text{RTMaps}^\text{®}$ data into a format readable by MATLAB. Figure 5.14 displays the components involved in the format conversion of LiDAR's data while 5.15 displays the components for format conversion of faceLAB, comfort sensor, GPS, lane and obstacle position and road images data.

Figure 5.14: Retrieving IBEO LiDAR’s data collected during the driving task
Table 5.2 below, shows the different components and their functions, involved in processing the driving data into MATLAB readable format. This driving data is later processed and converted into information related to the manoeuvres performed and their associated competency levels.

<table>
<thead>
<tr>
<th>Components</th>
<th>Performed Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>testLaserScanner_6</td>
<td>Reads the recorded driving scenario’s data for LIDAR (i.e. obstacle positions in the rear of the equipped vehicle) and converts the data in MATLAB readable format</td>
</tr>
<tr>
<td>scriptForMatlabFL_1</td>
<td>Reads the recorded driving scenario’s data for faceLAB (i.e. driver head and eye movements and position) and converts the data in MATLAB readable format</td>
</tr>
<tr>
<td>scriptForMatlabCS_7</td>
<td>Reads the recorded driving scenario’s data for comfort sensor (i.e. excessive acceleration/deceleration) and converts the data in MATLAB readable format</td>
</tr>
<tr>
<td>scriptForMatlabGM_6</td>
<td>Reads the recorded driving scenario’s data for GPS and MobileEye (i.e. vehicle position and lane/obstacle position in-front of the equipped vehicle) and converts the data in MATLAB readable format</td>
</tr>
<tr>
<td>scriptForMatlabImg_8</td>
<td>Reads the recorded driving scenario’s data for camera (i.e. images of the road ahead of the equipped vehicle) and converts the data in MATLAB readable format</td>
</tr>
</tbody>
</table>

Table 5.2: Name and function/purpose of the components involved in processing of the driving data
5.2.2 Manoeuvre Identification Module

Once all the required data has been acquired from the three mentioned variables (i.e. DVE) using the Data Registration Module (DRM), it is handed down to the Manoeuvre Identification Module (MIM). This is an integral module of Intelligent Driver Training System (IDTS) since it is responsible for converting the synchronised data into information.

This module uses the synchronised information over time and applies algorithms to automatically retrieve information about the driver gaze movement/fixation, lane positioning, following distances, test vehicle trajectory and distances from selected points on the road during the manoeuvres. It later utilises extended automata for decision making. The statistical analysis of timed events will help measure the performance of the driver.

For example, a state machine for a proper “lane change” behaviour will change states with events such as “mirror check”, “indicator on”, “head turn”, “wheel turn” and “road scanning”. The most critical part of this module is the time evaluation and synchronisation. Reason being, all the mentioned events for a proper lane change such as mirror, indicator on, head turn etc. are only valid if they were made at the right time. The details of calculations for gaze patterns and distances further used for manoeuvres identification and classification are followed.

5.2.2.1 Angle and Distance calculation

For most driving manoeuvres such as lane change, turn and overtake, vehicle trajectory calculation is required for detection. The spherical GPS coordinates are used to detect the angle and distances between the points. Along with this, the distance calculation is also an important aspect to determine if the manoeuvre was performed safely and within a required distance. The evaluation and management of sensor uncertainty is particularly necessary in a noisy multi-sensory context. Uncertainty of a GPS can pose many problems when dealing with the calculation of distances and angles between two locations. The estimation of GPS uncertainty and the resolution of this problem are provided below.
Estimation of GPS Uncertainty – As stated in Chapter 2, sensors collect data that are both incomplete (objects states are only partially measurable) and imperfect (measures are noisy). In order to make the most of the information sent by sensors, it is crucial to model the relation between objects true states and the corresponding observations made by sensors. Evaluation and management of sensor uncertainty is important in a multi-sensory environment. GPS uncertainty has to be measured to accurately map the trajectory of test vehicle (Sukkarieh et. al., 1999).

GPS provides the coordinates of a location with certain accuracy depending on its quality. When mapping the trajectory of a moving vehicle, it is important to be able to detect that given two GPS points, whether the second consecutive GPS coordinates represents a new position of the vehicle. Such an issue can be handled through the computation of the experimental variability of the GPS equipment used.

In-order to estimate the GPS uncertainty, the GPS was placed at a point and multiple recording (frequency 1Hz) were taken to obtain the numerical error variance of the GPS. Errors along the horizontal and vertical axis are independent and equal. So errors along one axis are normally distributed around zero with variance $\sigma^2$. Equation 1 was used to compute the variance along each axis separately. Then the maximum value is set as the variance $\sigma^2$.

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^{N} [calcDist(gps(i), meanGPS)]^2}$$  \hspace{1cm} \text{Eq. (1)}.$$

where N is the number of GPS points and $calcDist$ is the function that calculates the distance between two GPS points. Implementation of the function ‘$calcDist$’ which is using Haversine (Haversine) formula to calculate distance between two GPS points is described below.
Let $M_1(lat_1, long_1)$ and $M_2(lat_2, long_2)$ be the two points. And $O$ be the centre of the earth.

\[
\Delta lat = lat_2 - lat_1 \\
\Delta long = long_2 - long_1 \\
a = \sin^2\left(\frac{\Delta lat}{2}\right) + \cos(lat_1)\cos(lat_2)\sin^2\left(\frac{\Delta long}{2}\right) \\
c = 2a \tan\left(\sqrt{a} + \sqrt{1-a}\right) \\
dist = Rc
\]

**Table 5.3: Pseudocode/Implementation for calcDist for calculating distance between two GPS points**

where $lat_1$ and $lat_2$ are the latitudes for the first and second GPS points respectively. $long_1$ and $long_2$ are the longitudes for the first and second GPS points respectively. $R$ is the radius of the earth and $dist$ is the calculated distance between the two GPS points.

Errors being normally distributed means 95% of the coordinates obtained by the GPS are distributed within two standard deviations $\sigma$ around the true position (see Figure 5.16) (Gaussian distribution). Given a GPS set of coordinates, a 95% confidence interval (Davison, 2003, Chapter 3) for the true location can be obtained from the variance as follows:

\[
\text{calcDist}(GPS\text{.coordinates,TRUE.location}) \leq 2\sigma \quad \text{Eq.}(2).
\]

See implementation of ‘calcDist’

![Gaussian distribution](image)

**Figure 5.16: Gaussian distribution density function with mean $\mu$ and the variance $\sigma$**

Numerically, we obtain $\sigma^2 = 0.0272m^2$, which corresponds to a true location inside a circle of radius 32.9cm. In other words, two consecutive GPS points closer than 32.9cm cannot be considered as different.
Another issue related to the variability of GPS coordinates is that the direction of the moving vehicle given two consecutive GPS points can be insufficiently accurate for trajectory estimation (particularly in order to determine whether the vehicle is turning or not). In the worst case scenario the inaccuracy on the location estimation can lead to a difference in direction estimation by an angle $\theta$ as shown in Figure 5.17. Let $A$ and $B$ be the two absolute consecutive locations for a moving vehicle. In the worst case scenario, $A^-$ and $B^-$ represent the points obtained after the GPS error variance (of $2\sigma$) in A and B respectively. Thus we can say that inaccuracy of vehicle heading estimation is $\theta$.

For further analysis we require this angle to be small and we take $\theta=10^\circ$ as a threshold.

Figure 5.17: Calculation of Vehicle heading estimation $\theta$

The threshold distance $\text{threshold } \text{dist}$ is derived as follows:

$$\text{threshold } \text{dist}=2*\text{dist} \quad \text{Eq. (3)}.$$  

From Figure 5, we can calculate that the distance (dist) is:

$$\text{dist} = \frac{2\sigma}{\tan \theta} \quad \text{Eq. (4)}.$$  

Using Equation 3 and 4, we get:

$$\text{threshold } \text{dist} = \frac{4\sigma}{\tan \theta} \quad \text{Eq. (5)}.$$  

Numerically, we get $\text{threshold } \text{dist}=3.7m$. It means, two consecutive GPS points will be considered the same (i.e. the vehicle is stopped) if their distance is smaller than 3.7m. This threshold distance is useful in calculating the turn angle, as will be discussed in the following section.
**Turn Detection Algorithm** – Once the GPS error variance has been calculated, we compute an angle for every GPS point, in-order to determine the vehicle’s turn angle. The pseudocode for computing an angle for each GPS point (except for the first and last GPS point) is provided below:

Let $T$ denote a given time

For all GPS points and their corresponding recorded times

  Initialise $t$ as 2
  Store three GPS points in array $Y$ for time $T-1$, $T$ and $T+1$
  Compute the *distance* between GPS points at time $T-1$ and $T+1$

  While *distance* is less than threshold_distance (threshold_dist)
    Add GPS points in $Y$ array for time $T-t$ and $T+t$, if only GPS points exist for time $T-t$ and $T+t$
    Increase $t$ by 1
    Compute *distance* between GPS points at time $T-t$ and $T+t$
  End While

  If *distance* is greater than or equal to threshold_distance
    Compute the tangent angle $\theta$ for GPS point at time $T$ given $T-t$ and $T+t$
  End If

End For

With the above mentioned algorithm, every GPS point will have a tangent angle based on the points before and after it. Another point worth mentioning is that even though derivative computations amplify noise (Lubansky et. al. 2006; Machado and Galhano, 2008), in the calculation of the tangent angle for every GPS point, the distance between the GPS points that were below the threshold distance (threshold_dist) were ignored hence preventing noise in the estimation of the tangent angle. Ignoring the distance between the GPS points that are below the threshold helps the derivative computation to achieve less noisy results. As the
derivatives ($\frac{\Delta \alpha}{\Delta s}$) for the GPS points, whose distance ($\Delta s$) is less than the threshold distance are not computed allows to achieve smoother results thus reducing the noise that can be present due to the GPS receiver’s uncertainty.

Once the angle for every GPS point is calculated, the derivative of the angle with respect to the distance travelled ($\frac{\Delta \alpha}{\Delta s}$) is computed. $\Delta \alpha$ is the change in angle and $\Delta s$ is change in distance. This derivative is useful in eliminating those GPS points during which the car did not move a specified threshold distance. The method for computing the derivative $\frac{\Delta \alpha}{\Delta s}$ at each GPS point is very similar to the method for computing angle $\theta$ for every GPS point. For the pseudocode below, assume every GPS point now has an assigned angle as well (calculated using the above mentioned pseudocode).
Let $T$ denote a given time

For all GPS points and their corresponding recorded times

- Initialise $t$ as 2
- Store three GPS points in array $Y$ for time $T-1$, $T$ and $T+1$
- Compute the distance between GPS points at time $T-1$ and $T+1$

While distance is less than threshold_distance

- Add GPS points in $Y$ array for time $T-t$ and $T+t$, if only GPS points exist for time $T-t$ and $T+t$
- Increase $t$ by 1
- Compute distance between GPS points at time $T-t$ and $T+t$

End While

If distance is greater than threshold_distance

- Compute angle difference $\Delta \alpha$ between GPS points at time $T-t$ and $T+t$
- Compute the distance $\Delta s$ between GPS points at time $T-t$ and $T+t$
- Compute the derivative $\frac{\Delta \alpha}{\Delta s}$ for the GPS point $T$

End If

End For

Figure 5.18 presents the vehicle trajectory in blue, while the red line represents the derivative $\frac{\Delta \alpha}{\Delta s}$ for the respective GPS points. Based on these derivative values, the start, peak and end of the turn are segmented out. The start and end of the turn are crucial in finding out the centroid of the turn. This centroid is then used to calculate the ‘safe’ distance to switch on the indicator.

**Centroid Calculation For The Turn** – As mentioned above, the centroid calculation of the turns will be useful in identifying the ‘safe’ distance at which the driver switches the indicator before the turn. Usually, the exact start and exact end of the turn is debatable i.e. where do we decide that the car began to turn (e.g. when the driver started to turn the steering or when the car turned a significant angle). Therefore, after the derivatives $\frac{\Delta \alpha}{\Delta s}$ for the whole driving scenario have been
calculated, the turn is segmented out based on the start and end turn using heuristics. Once the turn has been segmented out from the driving scenario, its centroid is then calculated. Even if the exact start of the turn is ambiguous, the centroid of the turn will be always accurate.

The centroid of an area is similar to the centre of mass of a body. The centroid of the turn is calculated between the start and end of the turn (i.e. the turn area) using derivative $\frac{\Delta \alpha}{\Delta s}$ as a weight function $A_N$ (see equation 6). Calculating the centroid involves only the geometrical shape of the area. So the area is divided into multiple rectangles and using Equation 6 below, the centroid of the area is calculated.

$$C = \frac{\sum A_N C_N}{\sum A_N} \quad \text{Eq. (6)}.$$ 

where $C_N$ is the index of the $N^{th}$ GPS point in the turn area and $C$ is the centroid of the turn. Figure 5.18, illustrates the turn’s centroid for both turns in DRIVE 1. Other information, such as indicator start, indicator end and turn start/end are helpful in accurately modelling these turns.

Figure 5.18. DRIVE1 – Representation of vehicle’s GPS trajectory with two left turns (in blue) and the derivative values $\frac{\Delta \alpha}{\Delta s}$ plot for the corresponding GPS points (in red)

Figure 5.19, presents the turns involved in DRIVE 2. It consisted of three turns, first was a left turn followed by a right and finally a left turn. The derivative $\frac{\Delta \alpha}{\Delta s}$ values are plotted along Y axis and the number of GPS points around the X
axis. It is evident from the graph that using derivatives, the exact nature of the turn can be deduced e.g. whether it was a left or a right turn (based on the sign of derivative). This data can also be used to compute the vehicle turn angle. From the graph, it is noted that the turns can be segmented from the rest of the driving scenario using heuristics based on the derivative values. All this information coupled with indicator, gaze and lane-keeping data effectively model the turn scenario.

Figure 5.19: DRIVE 2 – Represents the derivative values $\Delta \alpha / \Delta s$ along Y axis and No. of GPS points on X axis.

The next section details the algorithm for fixation identification that is used to analyse driver gaze behaviour.

5.2.2.2 Gaze and Fixation Tracking

In this system, faceLAB is used for head and eye gaze tracking during the driving tasks. Eye movements in terms of fixations (pauses over informative regions of interest) and saccades (rapid movements between fixations) are important during driving (Pollatsek et al., 2006). Common analysis metrics include fixation or gaze duration.

The analysis of fixations and saccades requires some form of fixation identification, which is, the translation from raw eye-movement data points to fixation locations (and implicitly the saccades between them) on the visual display. Fixation identification significantly reduces the size and complexity of the eye-movement
protocol, removing raw saccade data points and collapsing raw fixation points into a single representative fixation.

Dispersion-threshold identification (I-DT) utilises the fact that fixation points, because of their low velocity, tend to cluster closely together. I-DT identifies fixations as groups of consecutive points within a particular dispersion, or maximum separation e.g., (Stark and Ellis, 1981; Widdel, 1984). Because fixations typically have duration of at least 100 ms, dispersion-based identification techniques often incorporate a minimum duration threshold of 100-200 ms (Widdel, 1984) to help alleviate equipment variability. The following I-DT algorithm is based on Widdel’s (1984) data reduction algorithm. The I-DT algorithm uses a moving window that spans consecutive data points checking for potential fixations. The moving window begins at the start of the protocol and initially spans a minimum number of points, determined by the given duration threshold and sampling frequency. I-DT then checks the dispersion of the points in the window by summing the differences between the points’ maximum and minimum x and y values; in other words, dispersion $D = [\max(x) - \min(x)] + [\max(y) - \min(y)]$. If the dispersion is above the dispersion threshold, the window does not represent a fixation, and the window moves one point to the right. If the dispersion is below the dispersion threshold, the window represents a fixation. In this case, the window is expanded (to the right) until the window’s dispersion is above the threshold. The final window is registered as a fixation at the centroid of the window points with the given onset time and duration. This process continues with the window moving to the right until the end of the protocol is reached.

Table 5.4 includes pseudocode for the I-DT algorithm. It should be noted that this characterization of fixations uses the centroid and diameter. A circular area is usually assumed and the mean distance from each sample to the fixation centroid provides an estimate of the radius. The I-DT algorithm requires two parameters, the dispersion threshold and the duration threshold, as shown in Table 5.4.
Set dispersion_threshold
Set duration_threshold
For all Gaze points
    Initialise window over first gaze points to cover the duration_threshold
    If dispersion of window points <= dispersion_threshold
        Add additional gaze points to the window until dispersion > dispersion_threshold
        Calculate/Note fixation at the centroid of the window points
        Clear window gaze points from the window
    Else
        Remove first gaze point from the window
    End If
End For
Return fixations

Table 5.4: Pseudocode for the Dispersion threshold identification for fixation identification

The fixations are calculated for all drivers to identify any specific gaze or fixation patterns that might belong to particular group of drivers.

5.2.2.3 Gaze Span Evaluation

The focus of this section is to assess drivers’ gaze pattern while they performed the selected manoeuvres. Figure 5.20 shows drivers’ fixations overlaid on an image of the road ahead while the drivers performed overtake manoeuvres. The image of the road in front was divided into five symmetrical segments to have a better understanding of the gaze patterns amongst different groups of drivers. These five segments helped in creating a histogram of the gaze on the road ahead. The gaze histogram was helpful in objectively evaluating the sections of the road that the driver focuses on while driving. These gaze patterns were evaluated for each part of the manoeuvre (i.e. Pre manoeuvre, During manoeuvre and Post manoeuvre).
CHAPTER 5. DESIGN OF INTELLIGENT DRIVER TRAINING SYSTEM

Figure 5.20 (a) Displays an experienced driver's gaze pattern during overtake on an image of road ahead. The yellow markers display the segmentation of the road ahead into five segments.

(b) Displays a novice driver's gaze pattern during an overtake manoeuvre.
(c) Presents the road image overlaid by a virtual scale such that it has 10 segments from the horizon to the car. This image is also used in creating the world model just once, which will be used to calculate the gaze depth and direction in future drives.
(d) Demonstrates the mapping of driver’s fixations (blue squares) on the road for a certain time on the road’s image.

Further explanation on the gaze span amongst different groups of drivers and their evaluations is presented later in Chapter 6 in sections ‘Analysis of turn’ and ‘overtake’.

5.2.2.4 Gaze Depth Evaluation

There is a need to recognise the difference in gaze patterns between novice and experienced drivers in order to identify any lack of competency amongst novice drivers. Pollatsek et al. (2006) found out, that novice drivers look less thoroughly for information than experienced drivers since novice drivers are less likely to glance at something new if they are already fixated upon some object.
The basic idea behind the gaze depth calculation is to first create a real world environment model of the road ahead of the driver given a priori information of the lane/road width. Once this model is created, a link between the image of the environment (shown in Figure 5.20-c) and the real world is established. Hence it enables the system to calculate the real world approximate depth (in metres) and orientation (in degrees), for each coordinate in the image with respect to its location in the real world. faceLAB measured the eye and head movement and synchronised the gaze data using timestamps. The gaze or fixation information from faceLAB was later mapped on the image of the real world (as viewed by the driver). This is shown in Figure 5.20-d. This enabled the gaze depth calculation module to calculate the real world approximate depth (in metres) for each of the gaze point, given its location on the image.

Combining the GPS location points for the trajectory of the driving scenario synchronised (i.e. time stamped using RTMaps) with the faceLAB gaze/head orientation data, along with accelerometer and vehicle dynamics data logged during the drive, made it possible to calculate an approximate GPS location for each category of data (i.e. faceLAB data, accelerometer data) collected. This synchronised data enabled the calculation of a GPS location for the driver’s fixation given the GPS location of the vehicle and the depth of their fixation. This enabled viewing of the driving information at a specific time ‘t’ of interest. The fixation depth data retrieved above from faceLAB for a specific time t is then converted into GPS points using Haversine formula.

Once the fixation points are converted into GPS points, a user interface was developed using Google map. The interface plots the vehicle trajectory and other driver’s gaze information such as eye gaze depth and orientation on Google map. The design of the gaze depth calculation and plot is presented in Figure 5.21. Figure 5.21 presents the design and block diagram of the gaze depth calculation and mapping module. The three sensors output information at different frequencies. The processing module is responsible for synchronising the multi-sensory data and computing the gaze/fixation depths for a given time. This processed information is then written to a file which is read by the mapping module. The mapping module is
responsible for plotting the processed gaze and vehicle information on GoogleMaps as the vehicle moves along.

![Diagram of the design for gaze depth calculation and mapping module](image)

**Figure 5.21:** Design for gaze depth calculation and mapping module

**Algorithm For Gaze Depth Calculation and Plotting**

![Diagram of the algorithm](image)

**Figure 5.22:** Describes the variables \((\Delta s, \Delta r, \mu_0, v_H, u, \text{ and } v)\) that is used in calculating the world model just once, which is later used to calculate the gaze depth and direction in future driving experiments.
Given the gaze plots on the image of the road ahead, the algorithm for computation of drivers’ gaze depth is presented as follows.

1. Set initial parameters just once \((\Delta \text{s}, \Delta \text{r}, \mu_0, \nu_H)\) shown in Figure 5.22, that are going to be used in the formula 5.5.6, 5.5.7, 5.5.8 (explained in the Table 5.5) to calculate the depths (i.e. x depth and y depth) of the gaze. These parameters (i.e. \(\Delta \text{s}, \Delta \text{r}, \mu_0, \nu_H\)) are calculated from the information retrieved from the actual road and the road’s image.

- \(\Delta \text{r}\) is the “actual distance” (in metres) transversally between two lane marking.
- \(\Delta \text{s}\) is the “actual distance” (in metres) longitudinally between the start of one lane divider marking and the second lane divider marking.
- \(U \text{ and } V\) are the baseline coordinates of the image.
- \(\mu_0 \text{ and } \nu_H\) are the corresponding x and y coordinate of the “road’s image”.

They represent the point where the lanes seem to merge together (i.e. the vanishing point on horizon).

2. Retrieve the eye gaze positions of the driver using gaze tracker.

3. Compute the eye fixations from the eye gaze data provided by gaze tracker.

4. Plot the eye gaze/fixations on the 2-D image of the road (i.e. we get the x, y of the gaze plots on the image).

5. Using statements 1.), 4.) and the equations 5.5.6, 5.5.7, 5.5.8 (in the Table 5.5), calculate the gaze depth along X axis and Y axis on the actual road.

6. Convert the gaze/fixation depths into GPS points using Haversine formula.

7. Plot the GPS point of the vehicle and the GPS points of the fixations on GoogleMaps.

Using data from the actual road and its image (i.e. a 2D image acquired from the camera mounted on the windscreen), enables the approximate calculation of the gaze/fixation depth and orientation (i.e. along X axis and Y axis) in the real world.

Equations 5.5.1, 5.5.2 and 5.5.3 are taken from (Maire, 2007)

\[
\mu = \beta_\mu \frac{x}{y} + \mu_0 \quad (5.5.1)
\]

\[
\nu = \beta_\nu \frac{1}{y} + \nu_H \quad (5.5.2)
\]
\[ v_p' = v_H + \left( \frac{\beta_v}{y_p} + \Delta s \right) \] (5.5.3)

From equation (5.5.2), for a specific point ‘p’ gives

\[ y_p = \left( \frac{\beta_v}{v_p - v_H} \right) \] (5.5.4)

Put equation (5.5.4) in eq. (5.5.3) gives

\[ v_p' = v_H + \left( \frac{1}{\Delta s} + \frac{1}{v_p - v_H} \right) \] (5.5.5)

Further processing equation (5.5.5) computes

\[ \frac{1}{v_p' - v_H} = \frac{\Delta s}{\beta_v} + \frac{1}{v_p - v_H} \] (5.5.6)

From equation (5.5.6) computation of \( \beta_v \) is possible when \( \Delta s, v_p' \) and \( v_H \) are known

Equation 5.5.7, 5.5.8 are from (Maire, 2007)

\[ \beta_u = \beta_v \times \left( \frac{m_{\text{RIGHT}2} - m_{\text{LEFT}2}}{\Delta r} \right) \] (5.5.7)

We compute \( \beta_u \) from equation 5.5.7 when \( \Delta r, \beta_v \) and slopes of right \( (m_{\text{RIGHT}2}) \) and left \( (m_{\text{LEFT}2}) \) lanes are given. The slopes can be found using eq. 5.5.8.

\[ m_{\Delta} = \frac{\Delta u}{\Delta v} \] (5.5.8)

**Table 5.5: Equations used for the calculation of driver's gaze depth**

### 5.2.2.5 Manoeuvre Segmentation and Classification

There are a number of events that frequently occur during driving. A typical driving scenario comprises of a certain set of driving events and patterns that are repeated over time. For example, a right turn manoeuvre is composed of tasks as shown in Table 5.6. The important aspect of manoeuvre performance assessment is to segment out particular manoeuvres from the driving scenario. The manoeuvres discussed in this thesis are the turn, lane change, T-crossing and overtake manoeuvres. In-order to effectively monitor the driver performance, every manoeuvre is divided into three parts namely: pre-manoeuvre, manoeuvre and post-manoeuvre. This helps to objectively assess the driver performance not just during manoeuvre but even at the approach and end of a particular manoeuvre.
The manoeuvres were selected because of their cost to the society in the event of crash. In Australia, 30% of crashes occur on road curves (Shields et. al., 2001). Crashes on road curves frequently result in fatal injuries or casualties. Curve related crashes contributed to 63.44% of fatalities (Queensland transport, 2006). In addition, the likelihood of surviving crashes on curved roads is approximately 17% lower than on straight roads (Queensland transport, 2006). Along with this, the other manoeuvre under consideration in this thesis is overtaking. Overtaking is considered to be a hazardous task, with experts estimating that lane change crashes including overtaking and lane merging account for 4 to 10% of all crashes (Hegeman et. al., 2005).

### 5.2.2.5.1 Turn and Curve Detection

As previously mentioned, the manoeuvres are segmented based on the spatiotemporal location of the vehicle. For example in order to determine whether the vehicle is passing through a turn, GPS data are used. This GPS data helps to compute a tangent angle for each GPS point returned for the driving scenario. Once the angle for every GPS point is calculated, the derivative of the angle with respect to the distance travelled {i.e. $\frac{\Delta \theta}{\Delta s}$ } is computed. Based on these derivative values, the start, centroid and end of the turn are segmented. Details are explained in section 5.2.2.1 (Angle and Distance Calculation). This start and end of the turn manoeuvre helps to better monitor driver performance just before and after negotiating the turn. Table 5.6, presents the tasks that driver trainers monitored during the turn. IDTS framework utilises the same tasks for competency assessment using fuzzy rule based system. Figure 5.23 below presents a turn manoeuvre.
In order to effectively model a turn manoeuvre, it is necessary to determine the complete demographics of a turn. IDTS calculates when the vehicle’s turn started, when it finished and determines the centroid and the angle of the turn (i.e. was it a 90 degree turn or 45 degree turn).

5.2.2.5.2 Lane change and Overtake

Apart from calculating the turn angle for the vehicle, the distance of vehicle with respect to the lane is also calculated using MobileEye (MobileEye). This enables the framework to determine the location at which the lane changes take place. A typical overtake on a right hand drive road/vehicle consists of a lane change to the right followed by a lane change to the left within a specific distance (as shown in Figure 5.23). This specific distance varies based on the speed of the vehicle. Gordon and Mast calculated this distance using the equation below (Gordan and Mast, 1970).

\[
D = 112.5 + 15.2V + 0.093V^2
\]

where \(D\) is the distance in feet and \(V\) is the velocity in miles per hour. Figure 5.24 presents a typical overtake scenario in which the red vehicle changes lane twice to overtake the green vehicle. As mentioned above, for complete monitoring of driver performance, every manoeuvre is divided into three parts. By doing this, the framework is able to analyse the driving performance for the approach to a manoeuvre, the actual manoeuvre and exit from the manoeuvre. This partitioning of each manoeuvre into three portions is based on the average speed of the test vehicle.

Figure 5.24: Lane changes identified by the red circles used for overtaking a vehicle (in green)
The following section will explain the final section of Intelligent Driver Training System (IDTS). This assessment and visualisation module is one of the key aspects of driver training programs. This can be either self-assessment or assessment from another group or individual.

### 5.2.3 Assessment and Visualisation Module

As mentioned previously, the safety criteria are an important phase of this intelligent driver training system. This phase requires a great deal of collaboration with the driver trainers to effectively pin down the important tasks in each driver manoeuvre.

The subsections provide a couple of driving manoeuvres that have been identified to be vital for driving. We hypothesise that most observable and measurable driving performances could be integrated comprehensibly in a safe performance protocol which in turn could be operationalised with the use of advanced technology.

For clarity, it should be stated that ‘highly competent’ driving is not a tangible or easily defined construct and therefore, a definition for ‘highly competent’ driving will be developed and made operational within this thesis. An example of a core driving competency may relate to maintaining a safe driving distance between vehicles and braking on approach to an intersection. A computer based analysis of the above basic behaviour can be articulated into a safety scale.

The main idea behind the classification of manoeuvres is that, given information about the driving situation (i.e. tasks executed) and knowledge about driver behaviour, it is possible to infer the manoeuvres that a driver is most likely to have performed. Figure 5.25 introduces a pictorial representation of the manoeuvre competency assessment. For example, when the framework identifies a lane change, the competency assessment of that manoeuvre is performed. This competency assessment is based on tasks such as:

- How many times did the driver check the mirrors before the lane change?
- What was the driver’s speed on approach of the lane change manoeuvre?
• Did the driver check the lane (by doing a head check) in which they were going to move?
• How long before the indicator was switched on before the lane change?
• Was the driver positioned in the lane properly before the lane change?
• Was the lane change manoeuvre performed smoothly (i.e. no excessive lateral or longitudinal forces)?

These tasks were identified based on driver trainers’ assessment of the drivers (see table 5.6). All these tasks help calculate the competency level of a particular manoeuvre. Another point highlighted in Figure 5.25 is that task assessments can be combined to create a manoeuvre assessment (represented as triangles) and some of the manoeuvre assessments can be further combined with other manoeuvres or tasks to create more complex manoeuvres’ assessments (i.e. T-Crossing or overtake). As presented below, overtake assessment is basically the union of:

• right lane change assessment
• left lane change assessment
• the assessment of rear end gap the driver had with the car being overtaken, at the time when driver moved into the left lane

![Figure 5.25: Manoeuvre performance assessment based on the tasks. Tasks are shown in ellipses and manoeuvres are represented as triangles.](image-url)
The benefit of such a modular approach is that it facilitates the evolution of further complex manoeuvres. It has been mentioned in Chapter 4 that Intelligent Driver Training System (IDTS) framework selected fuzzy set theory to define high competence driving models for different manoeuvres. The assessment protocol that IDTS used for evaluation of driving manoeuvres is presented in the next section.

5.2.3.1 Assessment Protocol

There are a number of events that frequently occur whilst driving. A typical driving scenario comprises of a certain set of driving events and patterns that are repeated over time. Driver instructors typically assess a certain set of skills to assess drivers during a driver training session. A variety of standard check lists are used to assess driving performance. For example, the analysis of a right-hand turn consists of observing a substantial number of subsets of behaviour. The breakdown of this particular behaviour as stated in a sample driver training manuals is shown in Table 5.6.

In the context of a driver training system, this list of driving behaviours will be assessed automatically through the combined information gathered from the Data Registration Module (DRM) and Manoeuvre Identification Module (MIM). Assessment such as the one described in Table 5.6 will be used to develop a safe performance protocol model that can be used to assess automatically, if the driving manoeuvres were performed in a highly competent manner.

<table>
<thead>
<tr>
<th>(Example of ) DRIVER EDUCATION PERFORMANCE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>Right Turn Assessment (Tasks List)</td>
</tr>
<tr>
<td>1) Checks mirrors.</td>
</tr>
<tr>
<td>2) Positions car properly in lane.</td>
</tr>
<tr>
<td>3) Signals right at the right distance from turn start.</td>
</tr>
<tr>
<td>4) Reduces speed and keeps wheels straight.</td>
</tr>
<tr>
<td>5) Checks traffic thoroughly, yielding to pedestrians.</td>
</tr>
<tr>
<td>6) Starts turn.</td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

Table 5.6: Driver Education Performance-Turn Assessment

A sample assessment manoeuvre that a driver trainer uses is presented in Table 5.6. For our proposed system, Action 1 (referring to table 5.7) can be detected by using
computer vision algorithms and systems that have already been implemented i.e. faceLAB. Action 2 can be detected by using lane change detection algorithms. Action 3 and 4 (referring to table 5.7) can be monitored using accelerometers and gyroscopic sensors. Accurate GPS positioning will also enable the system to detect car positioning. Therefore, it can be presumed that each task in a manoeuvre can be effectively captured using the technology at hand.

<table>
<thead>
<tr>
<th>Driving Tasks</th>
<th>Technology required</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Checks mirrors</td>
<td>FaceLab</td>
</tr>
<tr>
<td>• Positions car properly in lane</td>
<td>Mobile Eye</td>
</tr>
<tr>
<td>• Signals right</td>
<td>Sensor (accelerometer on indicator)</td>
</tr>
<tr>
<td>• Reduces speed and keeps wheel straight</td>
<td>GPS for speed, Sensors (accelerometer on wheel)</td>
</tr>
<tr>
<td>• Checks traffic thoroughly</td>
<td>FaceLab</td>
</tr>
<tr>
<td>• Starts turn</td>
<td>Sensor (accelerometer)</td>
</tr>
<tr>
<td>• Turns into proper lane</td>
<td>MobileEye</td>
</tr>
<tr>
<td>• Straightens wheel while maintaining</td>
<td>Sensor (accelerometer on wheel)</td>
</tr>
<tr>
<td>secure control</td>
<td></td>
</tr>
<tr>
<td>• Adjust speed to traffic flow</td>
<td>GPS and radar</td>
</tr>
</tbody>
</table>

Table 5.7: Driving tasks as monitored by in-vehicle sensors

Using such a system, an accurate measurement of the interaction between the driver, environment and the vehicle will be calculated. This will finally help in evaluating the competency of the driver and act as an assisting tool for the driver trainers.

5.2.3.2 Graphical Interface for Potential Feedback

Visualization of the driving tasks is an integral part of this research. Since its end users are driver trainers, it is necessary that all driving scenario’s data and low competence driving situations are represented in a way that is easy to comprehend. Hence, it will be easy for the driver trainers to explain some specific situation to the driver.
CHAPTER 5. DESIGN OF INTELLIGENT DRIVER TRAINING SYSTEM

Figure 5.26, presents an example of the vehicle trajectory and driving scenario’s data for Drive 1 (with two left turns). This interactive user interface helps drivers and their trainers to assess certain manoeuvres in a driving scenario by combining the multidimensional data acquired from DVE. By combining the numerical information from the graph in Figure 5.18, this interactive map (Figure 5.26) is able to show the distance between indicator switch on and the turn start/turn centroid. It is also able to show if during a manoeuvre, driver followed the lane keeping procedure. The visualisation module is explained in detail in Chapter 7.

![Figure 5.26: DRIVE 1 – Representation on map where indicator on (yellow) and indicator off (pink) were performed.](image)

5.3 Summary

In this chapter, a detailed architecture of the driver training system was introduced that will help the driver trainers in judging a manoeuvre’s performance. This design contained the three core components of this system, which were the Data Registration Module, Manoeuvre Identification Module and the Assessment module. These three components work together to synchronise, analyse and assess the safety of a certain manoeuvre.

The first part of this chapter explained the Intelligent Driver Training System (IDTS) concept. The following section explained the main modules involved in IDTS. The working of each module, and the tasks involved in each module are explained in detail in each module related section. These sections also elaborated on the problem of GPS uncertainty and its solution. They also presented the
techniques and pseudocode for computation of methods that are helpful in calculating tasks related to driving e.g. gaze/fixation position identification, multiple manoeuvre segmentation, test vehicle turn and distance computation and automated assessment of competence.

Since ADAS has never been comprehensively used to assess driving performance based on expert knowledge, the proposed training system addresses this gap by building upon traditional ADAS to deliver a comprehensive assessment of driving manoeuvres. This training system will eventually help driver trainers and its users to objectively evaluate and facilitate in potentially providing feedback to the novice drivers. The next chapter will explain in detail the making of the safe performance protocol. Using a rule based system, this protocol will help separate the manoeuvres conducted in a less competent manner from the ones conducted in a high competence manner.
Chapter 6

Developing a Driving Performance Protocol

There are many requirements for a road to be operated and managed properly but one of the most important requirements is that it should be safe for all to use. Although, every endeavour has been made to prevent crashes, there are still many crashes on the roads, and the first step in resolving this problem is to identify the low competence driving situations. Despite trying to develop a standard to assess competencies, there is no clear standard, due to the difficulty in evaluation of competency related to driving. Generally, road environment, driver and vehicle-related factors, or different combinations of these factors that cannot always be explained distinctly, contribute to crashes. This generates a problem that is characterised by uncertainty, subjectivity, imprecision and ambiguity in understanding what is actually a low competence level of driving. To solve this problem, fuzzy set theory can be used to deal with uncertainty and subjectivity of evaluating competency levels. The aim of this chapter is to model low and high competence levels for driving manoeuvres using fuzzy logic. As mentioned in the chapter (i.e. Chapter 4) related to driver performance, the primary strength of a fuzzy approach is that it is applicable in modelling human knowledge and the decision making process using a rule based approach. In this chapter, these rules that identify driving performance are initially designed with the help of expert knowledge (i.e. driver trainers). In order to fine tune these rules and the parameters that define these rules, a driving experiment was conducted to identify the empirical
differences between novice and experienced drivers after analysing the data recorded during the experiment. These differences were used to refine the fuzzy membership functions and rules that govern the assessments of the driving tasks.

Section 6.1 and 6.2 highlight the methodology of performance assessment using fuzzy logic. This section also presents the preliminary fuzzy sets and rules initially designed with the help of expert’s knowledge (i.e. driver trainers). This leads to the section 6.3, which reviews the driving experiment and focuses on its objective, method and the outcomes. Section 6.4 discusses the result of the driving experiment and fine tuning the fuzzy set parameters based on the results achieved from the driving experiment. This chapter concludes with a summary in section 6.5.

6.1 Performance Assessment Based on Fuzzy Logic

Driver perception and reaction processes are continuous over time and is modified to the environmental constraints. All inputs (related to the driving environment) presented to the driver while driving are not based on crisp values; rather they have some uncertainty based on subjective perception (i.e. distance from the turn, distance from the object in front, the position of a certain vehicle in future).

At an empirical level, uncertainty is an inseparable companion of almost any subjective or objective measurement, resulting from a combination of inevitable measurement errors, subjectivity and resolution limits of measuring instruments (Mendel, 2001). Fuzzy logic has been proven to deal with these uncertainties (Mendel, 2001). For example, a driver approaching an intersection when the green signal is changing to yellow, based on vague information about the time to reach intersection, performs the correct action which leads to a stop or pass safely at the intersection. Assume a driver is approaching the intersection at 30km/hr. The drivers’ decision is based on fuzzy inputs that can include the distance, speed to the intersection and vehicles on the road. Now his/her decision’s can be: a) adequate time to pass the intersection or b) not adequate, etc. Fuzzy logic seems to be closely related to the decision that is made by humans under uncertainty. Once more referring to the above example, the driver will not calculate the exact time left to cross the intersection rather an estimate based on the many factors such as speed of his vehicle, the distance till the intersection, how long has the signal been yellow for,
is the road clear after the intersection or it is blocked etc. Fuzzy logic makes it possible to imitate the behaviour of human logic, which tends to work with “fuzzy” concepts of truth.

Fuzzy logic is based on a three step process composed of fuzzification, inference and defuzzification. The fuzzification process is based on the membership functions. The role of the fuzzy membership functions is to represent subjective human perception using the concept of a fuzzy set (Lee and Donnel, 2007). In a classical set or crisp set, the objects in a set are called elements or members of the set. A characteristic function or membership function $\mu_A(x)$ is defined for any element $x$ in the universe $U$ having a crisp value of 1 or 0. This is shown in figure 6.1. For every $x \in U$,

$$\mu_A(x) = \begin{cases} 1 & \text{for } x \in A, \\ 0 & \text{for } x \notin A. \end{cases}$$

(1)

![Figure 6.1: Example of Classic set](image)

For the classical set or crisp set, the membership function takes a value of 1 or 0 if the element $x$ belongs to set $A$ or not respectively. For fuzzy set, the membership function can take any value in the interval [0, 1]. The value between 0 and 1 is referred to as the degree of membership (Bojadziev, 1995). A fuzzy set is characterised by several membership functions, $\mu_A$, defined as functions from the well defined universe $U$, into a unit interval, [0,1].

$$\mu_A : U \rightarrow [0,1]$$

(2)
As shown in Figure 6.2, the membership function represents the degree of the subjective notions of a vague class with an infinite set of values between 0 and 1 (Lee and Donnel, 2007). Hence, fuzzy logic extends conventional Boolean logic to handle the concept of the partial truth, the values falling between “totally true” and “totally false”. These values are dealt with using degree of membership of an element to a set. The degree of membership can take any real value in the interval [0, 1].

The inference part of the fuzzy logic is performed using fuzzy rules and is also known as Fuzzy Inference. A fuzzy rule has two components: an if-part (also referred to as the antecedent) and a then-part (also referred to as the consequent). These parts of the rules are also referred to as precondition (IF-part) and consequence (THEN-part). The precondition can consist of multiple conditions linked together with AND or OR conjunctions. Conditions may be negated with a NOT.

Fuzzy rule inference consists of two steps:

- Inferencing, which determines the fuzzy subset (see Figure 6.3, ‘inference’ label, high and medium risk subset) of each output variable for each rule. Usually MIN or PRODUCT are used as inference rules. Referring to Figure 6.3 label ‘fuzzification’, assume the two fuzzy sets ‘age’ and ‘car-power’ are defined as A and B respectively. The sets are described by their membership functions $\mu_A(x)$ and $\mu_B(x)$. The MIN inferencing or the fuzzy AND operator is defined as

$$\mu_{A \land B}(x) = \min \{\mu_A(x), \mu_B(x)\}$$

whereas the PRODUCT is defined as

$$\mu_{A \land B}(x) = \mu_A(x) \cdot \mu_B(x)$$
• Composition, which combines the fuzzy subsets for each output variable into a single fuzzy subset. Usually MAX or SUM are used in the composition phase. Referring to Figure 6.3 label ‘fuzzification’, assume the two fuzzy sets A and B are described by their membership functions $\mu_A(x)$ and $\mu_B(x)$. Using the MAX inferencing or the fuzzy OR operator is defined as

$$\mu_{A\lor B}(x) = \max\{\mu_A(x), \mu_B(x)\}$$

whereas the SUM is defined as

$$\mu_{A\land B}(x) = \mu_A(x) + \mu_B(x) - \mu_A(x)\mu_B(x)$$

Both MIN-MAX and PRODUCT-SUM combine the effects of the applicable rules and produce a continuous output (Kaehler, 1995). Therefore the MIN-MAX approach was selected for inferencing because of ease of implementation. The inference part using IF-THEN rules are a common way of representing and communicating knowledge in everyday conversation. Fuzzy rules offer a way of trading the precise representation of the values that the variables must assume, with much more intuitive fuzzy representations (Bojadziev, 1995). In binary logic the consequent is either true or false. In fuzzy logic partial truths are allowed so the consequent is as partially true as the antecedent allows it to be. In general a rule by itself does not do much, what matters are the set of rules that can match/compete with one another. The fuzzy inference methodology allows “fair” competition between these rules to produce sophisticated answers using seemingly simple assumptions (Kaehler, 1995).

The last stage is to convert the fuzzy output set to a crisp number (known as defuzzification). Two of the more common techniques are the Centroid and Maximum methods. In the Centroid method, the crisp value of the output variable is computed by finding the value of the centre of gravity of the membership function. Whereas in the Maximum method, the crisp value of the output variable is the maximum truth-value of the fuzzy subset. Figure 6.3 illustrates this complete process (i.e. fuzzification, MIN-MAX inference and defuzzification) with an example of computing drivers’ risk based on drivers’ age and car-power that the driver uses. This method can be similarly used for computing drivers’ competency for performing driving manoeuvres.
Using the example below, suppose for rule 1 (R1), the fuzzification of the age as 'young' produces 0.8 degree of membership with 'young' age and the car-power set as 'high' produces 0.4 degree of membership with 'high' car-power. Using the MIN operator, evaluation of the risk as 'high' will have a membership degree of 0.4 (i.e. minimum of (0.8 and 0.4)). Similarly, rule 2 (R2) will evaluate the risk as 'medium' with a 0.3 degree of membership with the 'medium' risk function.

The clipped membership functions, 0.4 ‘high’ risk and 0.3 ‘medium’ risk, resulting from the application of the rules (R1 and R2) are then merged to produce one final fuzzy set. This final fuzzy set is displayed in figure 6.3, label MAX composition. The MAX operation is used to merge overlapping regions. Finally, the Centroid is calculated for the resulting merged fuzzy set and this is presented in the Figure 6.3, label Defuzzification.

![Fuzzy Logic Diagram](image_url)

Figure 6.3: The three stages of the fuzzy logic (i.e. fuzzification, inference, defuzzification) using the MIN-MAX approach.

In this thesis, based on the identified objectives of the assessment model (presented in performance assessment Chapter 4), the factors (i.e. driving variables) that are of importance and the interaction of these factors allows to define the rules that assess competence.
6.2 Fuzzy Membership Functions

Generally, the methods of formulating fuzzy sets and its membership functions can be classified into three approaches: construction using the analyst's judgment or expert's knowledge, construction using experiments, or construction using a given numerical data set (Lee et al. 2006). Selecting a method to determine the membership functions depend on conditions that include the characteristics of the study and the available data set associated with the study. In this study, fuzzy sets and their membership functions are constructed based on expert’s knowledge about driving manoeuvres and later fine tuned by empirical observations from the driving experiment. The proposed system is designed to assist driver trainers (experts) in evaluating driver performance. For this reason, expert’s knowledge was initially utilised to design fuzzy rules and sets for driver behaviour evaluation. The driver trainers provided the tasks that are involved in a successful execution of a particular manoeuvre, this information combined with assessment rules was helpful in designing the assessment system. These rules were later refined using the results from the driving experiment. Following are the chosen tasks involved during driving manoeuvres for competency assessment. The tasks are:

- Lane positioning competency assessment.
- Indicator competency assessment.
- Following distance competency assessment.
- Gaze competency assessment.
- Check mirror competency assessment.
- Excessive acceleration or deceleration

Table I below introduces how the ‘fuzzy sets’ are utilised in assessing competencies for the ‘tasks’ that are involved in driving manoeuvres. The bottom up approach for evaluating driving manoeuvres for this research is presented in figure 6.4 (a) below.
Figure 6.4: (a) Representation of manoeuvre performance evaluation through bottom up approach using fuzzy sets
(b) Represents the relationship between manoeuvre evaluation, task evaluation and fuzzy sets

It illustrates the combination of multiple fuzzy ‘sets’ that help in evaluating competency assessment for a particular ‘task’. As illustrated in Table I below, the following distance task’s competency assessment is evaluated using the fuzzy sets *average speed* and *following distance*. Likewise, multiple ‘task’ competency assessments can be combined to evaluate a manoeuvre’s competency. This can be explained by choosing a turn manoeuvre, which is evaluated using the following tasks’ competency assessment: Lane positioning competency assessment, Indicator competency assessment, Gaze span competency assessment and Check mirror competency assessment.
### Table I: The tasks involved in the competency assessment of the driving manoeuvres and the fuzzy sets involved in the competency assessment of the tasks

<table>
<thead>
<tr>
<th>Tasks</th>
<th>Fuzzy sets</th>
</tr>
</thead>
<tbody>
<tr>
<td>Position in Lane</td>
<td>Vehicle position with respect to right lane for the manoeuvre</td>
</tr>
<tr>
<td>Indicator switch</td>
<td>Distance before turn/lane change where the indicator was switched on versus average speed of the vehicle during the manoeuvre</td>
</tr>
<tr>
<td>Check mirrors</td>
<td>Number of times mirrors are checked before undertaking of a manoeuvre</td>
</tr>
<tr>
<td>Following distance</td>
<td>Following distance maintained with the car in front on the approach to a manoeuvre versus average speed</td>
</tr>
<tr>
<td>Gaze Span</td>
<td>Number of fixations on the segments of the road ahead</td>
</tr>
<tr>
<td>Excessive accelerations</td>
<td>Number of excessive accelerations or decelerations during the manoeuvre</td>
</tr>
</tbody>
</table>

The details of these assessments are provided in section 6.4.2, 6.4.3 and Appendix A, B. Even though some of the tasks performed had no significant differences for novice and experienced drivers, yet these assessments were made for all the selected manoeuvres that were mentioned in Figure 5.22. These manoeuvres are turn, curve, lane change, overtake and T-crossing. In-order to monitor the drivers’ performance during a set of selected manoeuvres (i.e. turn, overtake etc), a driving experiment was conducted. The details of this study are given in the following section.

### 6.3 The Driving Experiment

The objective of this study was to study and assess driving competencies for both novice and experienced drivers using a 4WD. For this project, a driver training organisation (known as ‘Roadcraft’) located at Glenmire, Queensland agreed to provide the track for conducting the test drives. Figure 6.5 and 6.6 shows the test track used for this experiment. The author will like to acknowledge the assistance of MURCOTTS Pty Ltd. and its employees in selecting the driving manoeuvres and test track for the driving experiment. Detailed specifications of the study are presented below.
6.3.1 Ethical clearance

Ethical clearance for data collection for this experiment was gained from the QUT Human Research Ethics Committee. Details are given below:

**Title:** Characteristics of 4WD driving performance and driver behaviour.

**Ethics Number:** 4195H

**Ethics Category:** Human

6.3.2 Vehicle specifications

A Toyota 4WD was used as the test vehicle which the participants drove during the driving experiment. This vehicle was provided by QFleet and was equipped with the multiple sensors for evaluating the driving parameters. A second vehicle was used in overtaking manoeuvres. Specifications for the two vehicles used during the driving experiment are provided here.

- A 4WD vehicle (test vehicle) that contained the necessary sensors and laptops for monitoring the driving performance. The sensors included
  - MobileEye and IBEO Laser scanner for lane and obstacle detection
  - GPS and Vigil system for vehicle position and vehicle dynamics
  - faceLAB for tracking drivers head/eye movements
  - Cameras to record the images of the road ahead for gaze evaluation

  Details of the sensors and equipment fitted in the test vehicle are presented in Chapter 5 (section Recording scenario).

- A second vehicle (Toyota hatchback) was provided by Roadcraft and driven by RoadCraft’s driver. This vehicle was used in the overtake manoeuvres.

  Other than these two mentioned vehicles, there were no other vehicles on the test track.

6.3.3 Test track specifications

The driving experiment was conducted on a closed loop track. The pictorial representation of the track is presented in figures 6.5 and 6.6. Specifications for the test track/circuit are given below

- A fixed start point and end point from where the test vehicle starts and stops respectively.
• Clearly visible marked lanes (two lanes) for the execution of the overtake manoeuvres. The straight stretch of the track was approximately 150 metres long for execution of overtake manoeuvre at 50km/h (maximum limit). The vehicle being overtaken was set to have a maximum speed of 25km/h.

• Clearly visible marked lanes for manoeuvring a left turn on T-junction.

• Clearly visible marked lanes for a road curve/turn manoeuvres.

### 6.3.4 Experimental Conditions

Participants were tested individually on the closed loop test track for approximately one hour per session. Each participant drove the two laps (i.e. Figure 6.5 and 6.6) ten times. Testing times were scheduled at 9am, 11am and 1pm under clear weather condition. Each participant chose a testing time for which they felt they were the most alert. Using the parameters for this experiment (i.e. repetitive measures and standard deviation of observations), the power of the experiment using the Power Analysis and Sample Size (PASS) statistical tool was found to be 0.62.

### 6.3.5 Participants

Three experienced drivers (i.e. driver trainers) were selected from the driver training school (Roadcraft). The experienced drivers had an average of 20 years of driving experience. The inexperienced drivers (i.e. novice drivers) were recruited from the locality of Gympie, Queensland. The novice drivers were three male participants, each having a driving licence for less than two years and less than one year of on-road driving experience. All drivers had a valid driving license. Along with this, one driver trainer was recruited for the vehicle that was used for overtaking manoeuvres. Another driver trainer was recruited to monitor the participants and provide subjective assessments.

Each participant was given two test laps to allow them to become familiar with the track and start/stop locations. The setting up of sensors and profile creation for each participant was finalised before the test laps. All subjects provided written consent for this study which was approved by QUT ethics committee. Participants were paid AUD $50 for completing the driving sessions.
6.3.6 Procedure

The participants drove a Toyota 2007 Land Cruiser (i.e. 4WD). The track used for the test drive is presented in figures 6.5 and 6.6. The drivers’ eye/head movement along with vehicle dynamics and lane/obstacle positioning was recorded. Each driving task was divided into two loops. Each loop started and stopped at the positions identified in figures 6.5 and 6.6. The maximum speed limit for driving on this track was set to 50km/h.

Before the start of the experiment, each drivers’ face model was created using faceLAB for eye/head tracking. Furthermore, drivers’ details such as age, driving experience (in number of years), gender, were recorded. The information collected was treated in a confidential manner. Each driver was also briefed about the track geometry and the driving manoeuvres they would have to perform.

- First Lap
  In the first lap, drivers were instructed to turn left at the T-crossing. After going through the ‘curve’, the drivers overtook a vehicle that was in position (as shown in Figure 6.5 ‘2nd car’). “Point 1” is a reference point for the driver in the “2nd car”. The moment the 4WD/test vehicle reached this reference point, the driver of the “2nd Car” started to drive and did not drive at more than 25km/h. The driver of the 4WD after overtaking the ‘2nd Car’ stopped at the point shown in Figure 6.5.

  After completely stopping at the designated point (see Figure 6.5), the driver of the 4WD/test vehicle positioned the car for the second loop of the driving scenario (see ‘Start’ position in Figure 6.5).
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Figure 6.5: First Loop of each driving scenario (First lap).

- Second Lap
  The start point of the second loop is pointed out in Figure 6.6. In this loop the driver once again overtook the “Car 2” that was travelling at no more than 25km/h. After the curve of the track, the 4WD/test vehicle drivers made a left turn and stopped at the designated position as pointed out in Figure 6.6. Each driver had to complete all laps (i.e. two loops) and the selected manoeuvres ten times.

Figure 6.6: Second Loop of each driving scenario (second lap).

- Data Collection
  Data was collected at a high frequency (varying frequencies (ranging from 1Hz – 55Hz) of sensory data obtained from the car, the environment and the driver). Data from GPS was retrieved at 1Hz, vehicle dynamics and lane/obstacle monitoring system at 5Hz, driver’s head and eye gaze data at 55 Hz, cameras at 30Hz, laser
scanner at 50Hz. The data collected from the three components of driving is given below in Table 6.1.

<table>
<thead>
<tr>
<th>Vehicle</th>
<th>Driver</th>
<th>Environment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Speed</td>
<td>Head position</td>
<td>Lane position of the test vehicle</td>
</tr>
<tr>
<td>Brake</td>
<td>Gaze position</td>
<td>Obstacle position in-front of test vehicle</td>
</tr>
<tr>
<td>Indicator state</td>
<td>Excess acceleration</td>
<td>Obstacle position behind the test vehicle</td>
</tr>
<tr>
<td>Excess deceleration</td>
<td>GPS location</td>
<td></td>
</tr>
</tbody>
</table>

Table 6.1: Data (driving variables) collected during the experiment / study

### 6.4 Construction of Fuzzy Membership Functions

This section covers the results obtained from the driving experiment and the fine tuning of fuzzy membership functions to assess driving manoeuvres. The membership functions were initially created based on expert’s knowledge regarding the driving tasks (i.e. speed of the test vehicle, lane position of the vehicle, indicator switch on before a particular distance before the turn etc.). These variables relating to driving tasks were gathered using multiple sensors mounted on the test vehicle. This empirical data allowed further analysis and calibration of the membership functions. The significant differences between the novice and experienced (driver trainers) drivers as they perform the manoeuvres are highlighted in the sections below. These differences were later utilised to create fuzzy membership functions that can differentiate novice and experienced drivers. As already mentioned in Chapter 4 related to the review of driver performance, driver trainers are more proficient than novice drivers, therefore trainers driving will result in less loss of control of the vehicle or driving task. Given this reason, the driving data related to the manoeuvres undertaken by the trainers is considered to be of high competence level. The driver trainers’ knowledge was utilised to create the other competency classifications (i.e. high, medium, very high and very low).

As mentioned in the previous chapter, for a comprehensive evaluation of the driving manoeuvres, every manoeuvre is automatically divided into three parts by the Intelligent Driver Training System (IDTS) namely - pre-manoeuvre, manoeuvre and post-manoeuvre. This assisted in objectively assessing driver competency not just during the manoeuvre but even at the approach and end of a particular manoeuvre.
Another technique utilised for effective monitoring of drivers’ gaze pattern in this evaluation system is to divide the fixations into histograms based on their location on the road image ahead. The image of the road in front was divided into five symmetrical segments (i.e. segment 1 to 5, 1 being the left most and 5 being the right most) to have a better understanding of the gaze patterns amongst different groups of drivers.

To quantify the differences in driving tasks/manoeuvres between novice and experienced drivers, Generalised Linear Models (GLMs) were used. GLMs were helpful in identifying the effect of multiple factors on each other, factors being driving variables (i.e. experience, gaze pattern, speed, lane distance, following distance). GLMs from the Poisson and Gaussian family were fitted to model the expected value for the factor of interest knowing the other influencing factors. For example in Table 6.2, speed is the influenced factor where as the influencing factors are inexperience, speed for the pre-manoeuvre and the fixations in the 5th segment. Essentially, GLMs allow to model the factor of interest as a function of the different other contributing factors. Using such models permit the identification of influenced factors (e.g. gaze, lane distance) given the contributing factors (e.g. experience, speed etc.)

The formula below models the relationship between the factor of interest and the different influencing factors using GLMs.

\[
\begin{align*}
\eta &= \sum_i \beta_i \cdot \text{contributing Factor}_i \quad \rightarrow (a) \\
E(\text{factor of interest}|\text{contributing Factors}) &= \exp(\eta) \quad \rightarrow (b)
\end{align*}
\]

where Factor\(_i\) is the value of the contributing factor and \(\beta\) is the estimate for the factors (refer to Table 6.2-6.10). In order to compute the expected number for the influenced factor, (a) returns \(\eta\) (eta) which is a linear combination of the factors that needs to be investigated. The link function logarithm is used to model the relationship between the linear predictor (eta) and the influenced factor given the influencing factors. This is presented in (b) using the inverse link function (exp).

The following sections will present the analysis of the turn and overtake manoeuvres conducted using the driving experiment.
6.4.1 Analysis of Turns and T-Crossings Factors

The turns and T-crossing that were performed by both group of drivers (i.e. experienced and novice) are illustrated in the figures 6.5 and 6.6. The T-crossing manoeuvre was presented in the first lap whereas the turn was introduced in the second lap. The manoeuvre identification module was able to segment the turns based on the algorithms presented in section 5.2.2.1 ‘turn and distance calculation’. The recorded data (related to driver, vehicle and environment) for these turns were also segmented out from the complete driving data by the manoeuvre identification module.

Once the data were segmented, the differences in the data (i.e. factors) and their relationship with each other were quantified using Generalised Linear Model (GLM). GLMs show that amongst the driving factors studied, there were no statistically significant differences (p-value p > 0.05) between the experienced and novice drivers on the turn manoeuvres for the following factors:

- Indicator was switch on at a particular distance before the turn
- Excessive acceleration/deceleration
- Checking of mirrors

The other factors influencing driving performance are given with their log-odds as well as their p-value in Tables 6.2 to 6.5 for the turn and T-crossing manoeuvres. The level of statistical significance as assessed by p-value is represented by the number of ‘*’ in the tables.

The impact of the different factors obtained using GLM, for evaluating speed during the left turn at t-crossing, is summarized in Table 6.2. It identifies speed during the turn as a factor that is statistically significantly different (p<0.001) between the experienced and novice drivers. Other factors that contributed to speed (km/h) are speed during the pre-turn (i.e. pre-manoeuvre) (p<0.001) and the number of fixations (p<0.001) that the driver had during the turn manoeuvre. It has to be noted that segment 5 is the right most segment of the image of the road ahead (see Figure 6.7). The turn/t-crossings during the driving experiment were left turns.
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It shows that experienced drivers had more fixations on the far right of the road images (i.e. checking the right of the road when turning left on a T-crossing) as compared to their novice counterparts. Furthermore, the speed during the turn manoeuvres for novice drivers is slower compared to experienced drivers.

![Figure 6.7: The segmentation of the road ahead into five segments as viewed by the fisheye lens camera](image)

Table 6.3 below presents the factors that influence the time a driver stops at the ‘stop’ sign for a T-crossing manoeuvre. Inexperience (p-value< 0.001) is one of the significant factors that differentiate drivers for the stop time (seconds) at T-crossing. The analysis further reveals that the stop time is also influenced by the speed and the gaze locations on the road.

<table>
<thead>
<tr>
<th>Factors</th>
<th>Estimate (β)</th>
<th>Std. Error</th>
<th>p-value</th>
<th>Code</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept (Ω)</td>
<td>15.29301</td>
<td>2.95057</td>
<td>0.0005</td>
<td>***</td>
</tr>
<tr>
<td>InExperience</td>
<td>-8.40765</td>
<td>2.11219</td>
<td>0.0032</td>
<td>**</td>
</tr>
<tr>
<td>Speed-Pre</td>
<td>0.5899</td>
<td>0.07079</td>
<td>1.60E-05</td>
<td>***</td>
</tr>
<tr>
<td>Segment5-Post</td>
<td>0.5314</td>
<td>0.14198</td>
<td>0.0046</td>
<td>**</td>
</tr>
</tbody>
</table>

Signif. codes: p-val< 0.001*** p-val< 0.01** p-val< 0.05 *

*Inexperience: The novice driver
*Speed-Pre: Speed on the approach to a turn manoeuvre (pre-maneuvre/turn)
*Segment5-Post: Gaze fixations in segment 5 of the road ahead during post manoeuvre

Since it is apparent from Table 6.2 that the speed for turn manoeuvres is slower for novice drivers, combining this information with Table 6.3 indicates that novice drivers tend to stop for a smaller amount of time as compared to their experienced counterparts.
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Table 6.3: Linear regression estimates for factors influencing stop time at T-crossing during the driving experiment

*Inexperience: The novice driver
*Speed-Pre: Speed on the approach to a turn manoeuvre (pre-manoeuvre/turn)
*Segment 1 and 3: Gaze fixations in segment 1 and 3 of the road ahead during the t-crossing

Table 6.4 below shows the relationship between the distance of the test vehicle from the right lane (in cms) and other driving factors monitored during the turn manoeuvre. Even though there was no significant difference between the novice and experienced drivers for the distance during the turn, it can be observed that a relationship between the lane distance given the lap count and the position of the driver’s fixations was detected.

Table 6.4: Linear regression estimates for factors influencing lane distance at Turn during the driving experiment

*Turn (Second Lap): The left turn during the second lap of the driving experiment
*Segment 1, 2 and 4-Pre: Gaze fixations in segment 1, 2 and 4 of the road ahead during the pre-turn manoeuvres

Another notable difference was observed in the duration of fixations for both categories of drivers, see Table 6.5. Experienced drivers showed a tendency to vary their fixation duration a lot more than the novice drivers. Novice drivers would fixate for the same amount of time on a tight gaze span, whereas experienced drivers vary their fixations more, thus adapting with the changing driving conditions.

Table 6.5: Linear regression estimates for factors influencing variation in fixations

Factors | Estimate (β) | Std. Error | p-value | Code |
--- | --- | --- | --- | --- |
Intercept (β) | 8.7118 | 0.4538 | < 2e-16 | *** |
InExperience | -3.4785 | 0.6731 | < 2e-16 | *** |
6.4.2 Turns and T-Crossings Assessment

As previously stated, the tasks assessed for the selected manoeuvres include Lane positioning competency assessment, Indicator competency assessment, Forward collision competency assessment, Gaze span competency assessment and Check mirror competency assessment. This section designs the membership functions and the fuzzy rules to assess the competency of these tasks.

![Membership functions for competency assessment](image)

**Figure 6.8. Fuzzy membership functions for competency assessment. Very Low (VL\_C), Low (L\_C), Medium (M\_C), High (H\_C), Very High (VH\_C)**

Figure 6.8, represents the fuzzy membership functions for competency assessment of all the individual tasks mentioned above. Y axis represents the membership degree for the fuzzy sets, whereas X axis represents the competency factor. The competency is evaluated on a scale of 0-1, 1 being the lowest competence. The values of the membership functions (i.e. a, b, c, d, e,….h) were defined in a symmetric manner and later normalised between 0 and 1.

For each of the task performance assessments, the fuzzy sets were identified based on expert’s knowledge (i.e. driver trainers). The fuzzy sets are composed of membership functions that categorize the data. The membership functions for the different sets are defined in a way that driver trainers’ belonged to the ‘Medium’ membership function for each antecedent (calculated parameters from the driving manoeuvres i.e. average speed, distance, following distance and gaze span). The variance of the antecedents for the trainers was used to define the range of the medium membership function. The same variance was used, in case of no statistically significant difference between novice and experienced drivers, to create the low and high membership given the inexperienced drivers’ data from the driving experiment. In-case of a statistically significant difference in terms of driver's
behaviour using GLMs, the GLMs’ predictions were utilised in creation of the membership functions.

**Indicator Competency Level**

Even though there was no statistically significant difference detected between novice and experienced drivers for the indicator-switch-on-distance-before-the-turn manoeuvre, calculation of the indicator competency is still an important aspect for monitoring drivers according to driver trainers. The fuzzy sets involved in computing the indicator competency are:

- The average speed of the test vehicle to the start of the turn.
- AND
- Distance from the indicator start to the turn start.

Table 6.6 presents the consequents (competency) based on the antecedents (calculated parameters from the driving manoeuvres i.e. average speed and distance). The figures 6.9 (a and b) illustrates the fuzzy sets and the membership functions for these sets in detail.

<table>
<thead>
<tr>
<th>Avg. Speed from a particular distance to turn start</th>
<th>Distance (meter) from indicator to turn start</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>Medium</td>
</tr>
<tr>
<td>High_Compt.</td>
<td>High_Compt.</td>
</tr>
<tr>
<td>Medium</td>
<td>VeryHigh_Compt.</td>
</tr>
<tr>
<td>Medium_Compt.</td>
<td>Medium_Compt.</td>
</tr>
</tbody>
</table>

Table 6.6: The fuzzy rules for evaluating the indicator competency level.

*Compt.: competence

This competency is calculated by comparing the ‘safe distance’ (between indicator and turn start) against the average speed of the test vehicle to the turn manoeuvre. The rows in Table 6.6 depict average speed of the test vehicle to the turn. The fuzzy sets for the average speed are Low, Medium and High. Low speed fuzzy set is defined between 0-20 km/h. Medium is defined between 40-60km/h and speeds above 80km/h are high. Figure 6.9-a presents this in a pictorial form.

The columns in Table 6.6 represent the distance where the indicator was switched on to the turn start. The distance is described by fuzzy sets Medium, Medium_High/Low, Very_High/Low. The ‘Medium’ distance is defined to be between 30-40 metres. The ‘Med_HL’ (medium high or medium low) distance is
defined between 45-55m or 15-25m. This means that the indicator should not be
turned on too close or too far away from the turn start. The distance that does not
lie in ‘Medium’ or ‘Med_High/Low’ fuzzy sets is in the ‘V_HL’ (very high/ very
low) distance fuzzy set. Figure 6.9-b presents this in a pictorial form. Some of the
fuzzy rules from Table 6.6 for assessing indicator competency level for turn
manoeuvre are:

- IF Avg. speed is ‘Low’ and Distance is ‘Medium’ then competency is ‘High’
- IF Avg. speed is ‘High’ and Distance is ‘Med high/Low’ then competency is
  ‘Medium’

![Figure 6.9: (a) Average speed of test vehicle for pre-turn manoeuvre](image)

![Figure 6.9: (b) Distance (meter) from indicator start to turn start](image)

It should be pointed out that since indicator is switched on before the start of the
turn (i.e. pre-turn manoeuvre), therefore no indicator competence is computed for
the turn and post-turn manoeuvre.

The analysis of the indicator competency level for the turn manoeuvre is presented
in Table 6.6 and Figure 6.9. Since the type of the membership functions (i.e. trapezoidal) is the same for other tasks’ competency assessment for turns, the fuzzy
sets and the inference rules are presented in Appendix A. The Appendix A includes:

- The pictorial representation of fuzzy sets and the membership functions for
evaluating the competency involved in performing lane keeping, forward collision
and gaze tasks.
- The rules (in tabular form) that are used to evaluate the competency involved in
each part of the turn manoeuvre (namely pre-manoeuvre, manoeuvre and post-
manoeuvre) for a given task.
6.4.3 Analysis of Overtake Manoeuvre Factors

This section presents the analysis of the different driving variables that were recorded and later analysed to identify differences in novice and experienced drivers performance in overtake manoeuvres. Similar to the turn manoeuvre, the overtake manoeuvre was performed by both group of drivers. The overtake manoeuvres are pointed out in figures 6.5 and 6.6. The drivers had to overtake one vehicle that was present in each lap of the two lap circuit. The manoeuvre identification module was able to segment out the overtake manoeuvres based on the algorithms presented in section 5.2.2.1 ‘turn and distance calculation’ combined with heuristics based on the lane positioning and the indicator status.

For the overtake manoeuvres, Generalised Linear Models (GLMs) show that amongst the driving factors studied, the following factors were not significantly different (p-value p > 0.05) for the experienced and novice drivers during an overtake manoeuvre. Factors associated with p-value (p > 0.05) are considered to show no statistically significant relationship between factor of interest and the influencing factors.

- Indicator was switch on before lane changes for the overtake
- Following distance before the overtake
- Excessive acceleration/deceleration
- Checking of mirrors

Tables 6.7 to 6.9 identify the factors of interests that distinguish novice and experienced drivers’ performance in the overtake manoeuvres. Table 6.7 identifies one of the factors of interest differentiating novice and experienced drivers during their overtake manoeuvre. The factor of interest in Table 6.7 is the lane distance from the right lane while the test vehicle was overtaking the 2\textsuperscript{nd} vehicle (i.e. when the test vehicle was in the right lane). It can be observed that inexperienced drivers tend to be further away from the right lane as compared to experienced drivers (p<0.0001). During the overtake manoeuvre (i.e. manoeuvre stage), when the novice drivers are passing the overtaken vehicle, they tend to be closer to the left lane. Hence, this demonstrates that novice drivers pass closer to the vehicle being overtaken compared to experienced drivers.
CHAPTER 6. DEVELOPING A DRIVING PERFORMANCE PROTOCOL

Factors | Estimate ($\beta$) | Std. Error | p-value | Code |
---|---|---|---|---|
Intercept (\(Y\)) | 96.906 | 1.883 | \(< 2e-16\) | *** |
InfExperience | 23.356 | 2.837 | 3.08E-13 | *** |

Signif. codes: p-val= 0'***' \ p-val < 0.001'**' \ p-val < 0.01'*' \ p-val < 0.05 ' ' 

Table 6.7: Linear regression estimates for factors influencing distance from the right lane at overtake during the driving experiment

Another factor distinguishing the novice and experienced drivers during the analysis of the overtake manoeuvres is presented in Table 6.8. It shows that the time spent in the right lane whilst overtaking is less for inexperienced drivers. This demonstrates that as novice drivers are passing the vehicle to be overtaken using the right lane, they tend to stay in the right lane for a shorter amount of time as compared to their experienced counterparts.

Factors | Estimate ($\beta$) | Std. Error | p-value | Code |
---|---|---|---|---|
Intercept (\(Y\)) | 7.5375 | 0.1305 | \(< 2e-16\) | *** |
InfExperience | -0.7203 | 0.1871 | 0.000204 | *** |

Signif. codes: p-val= 0'***' \ p-val < 0.001'**' \ p-val < 0.01'*' \ p-val < 0.05 ' ' 

Table 6.8: Linear regression estimates for factors influencing time spent in right lane at overtake during the driving experiment

Table 6.8 identifies the gaze span difference between inexperienced and experienced drivers during the overtake manoeuvre. It was observed that novice drivers focused solely on the 3rd region (i.e. middle of road ahead), while experienced drivers had a much wider gaze span during overtake. Another observation was that novices were generally more focused than experienced drivers to fixate their gaze only on the road far ahead (i.e. close/above the horizon) instead of fixating on road. Such gaze pattern was consistently noticed in each part of the manoeuvre (i.e. Pre overtake, During overtake and Post overtake). The impact of the different factors obtained using GLM for evaluating gaze span are summarised in Table 6.9 below.

Factors | Estimate ($\beta$) | Std. Error | p-value | Code |
---|---|---|---|---|
Intercept (\(Y\)) | 3.97719 | 0.0291 | \(< 2e-16\) | *** |
Inexperienced | -0.78733 | 0.04504 | \(< 2e-16\) | *** |
OT Manoeuvre | 0.67727 | 0.02202 | \(< 2e-16\) | *** |
Post OT Manoeuvre | -0.66212 | 0.03074 | \(< 2e-16\) | *** |
Segment2 | -0.23887 | 0.03526 | 1.24E-11 | *** |
Segment3 | 2.09423 | 0.04752 | \(< 2e-16\) | *** |
Segment4 | -0.42173 | 0.07999 | 1.35E-07 | *** |
Segment5 | -0.82046 | 0.09276 | \(< 2e-16\) | *** |
Inexperienced – Segment3 | -1.20267 | 0.05166 | \(< 2e-16\) | *** |
Inexperienced – Segment4 | -0.79411 | 0.09381 | \(< 2e-16\) | *** |
Inexperienced - Segment5 | -0.53378 | 0.10651 | 5.40E-07 | *** |

Signif. codes: p-val= 0'***' \ p-val < 0.001'**' \ p-val < 0.01'*' \ p-val < 0.05 ' ' 

*OT – Overtake

Table 6.9: Linear regression estimates for factors influencing gaze span
Table 6.9 shows that experienced and inexperienced drivers had a significant difference in gaze span while performing the overtake manoeuvre. The largest gaze difference amongst the two groups was noticed in the 1st, 2nd and 3rd segments of the road image. Novice drivers tended to look a lot less in the 1st and 2nd segment as compared to the experienced drivers. Along with this, novice drivers looked more in the 3rd segment as compared to the experienced drivers. These results are consistent with the previous research which stated that horizontal variance in gaze was greater for experienced drivers (Bojadziev, 1995). This enabled the creation of fuzzy sets and rules to identify gaze patterns competency assessment, presented in the section below.

As mentioned previously, experienced drivers show more horizontal transitions than novice drivers. Along with this, the other notable difference was observed in the duration of fixation for both categories of drivers. Experienced drivers tend to vary their fixation duration a lot more than novice drivers. Novice drivers tend to fixate for the same amount of time on a tight gaze span, whereas experienced drivers vary their fixations more hence adapting with the changing driving conditions. The impact of the different factors obtained using GLM for evaluating fixation durations is summarised in Table 6.10 below.

<table>
<thead>
<tr>
<th>Factors</th>
<th>Estimate ($\hat{\beta}$)</th>
<th>Std. Error</th>
<th>p-value</th>
<th>Code</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept (V)</td>
<td>8.7118</td>
<td>0.4538</td>
<td>&lt; 2e-16</td>
<td>***</td>
</tr>
<tr>
<td>Inexperienced</td>
<td>-3.4785</td>
<td>0.6731</td>
<td>&lt; 2e-16</td>
<td>***</td>
</tr>
</tbody>
</table>

Signif. codes: p-val = 0*** p-val < 0.001** p-val < 0.01* p-val < 0.05

Table 6.10: Linear regression estimates for factors influencing variation in fixations

6.4.4 Overtake Manoeuvre Assessment

This section presents the design of membership functions and the fuzzy rules to assess the competency of the tasks that compose an overtake manoeuvre. The tasks are: Lane positioning, Indicator, Forward collision, Gaze, Check mirror. A detailed explanation of the gaze span assessment is presented below. Since the type of the membership functions (i.e. trapezoidal) is the same for other tasks’ competency assessment for overtake manoeuvres, the fuzzy sets and the inference rules are presented in Appendix B.
Gaze Span Competency Level

Figure 6.10 presents the trapezoidal membership functions and their relationship for the number of fixations on the different segments of the road ahead. These membership functions have been created after analysing the difference in gaze patterns between novice and experienced drivers. GLMs estimate of the drivers’ gaze and the standard deviation between the gazes for both groups of drivers, assisted in designing the membership functions.

Table 6.11 along with Figure 6.10 is utilised to assess the competency for “gaze pattern” task. This assessment is a necessary component to gauge multiple manoeuvres’ (i.e. turn, overtake, T-crossing) competencies. The fuzzy sets involved in computing the gaze competency are:

- Fixations in 1st and 2nd segment of the road ahead
- Fixations in 3rd segment of the road ahead.

In Figure 6.10, X axis represents the membership functions and their relationship for the fuzzy set, whereas Y axis represents the degree of membership to the functions (i.e. Low (L), Medium (M), High (H)). The competency is evaluated on a scale of 0-1, 1 being the lowest competency level.

Table 6.11 presents the fuzzy rules for gaze competency assessment. As mentioned above, novice drivers look less in the 1st and 2nd segment as compared to experienced drivers during the overtake manoeuvre and more in the 3rd segment as compared to experienced drivers. The gaze competency assessment is evaluated by comparing the number of fixations in the 1st and 2nd segment of the road (shown in Figure 6.8) against the number of fixations in the 3rd segment of the road.

Some of the fuzzy rules from table 6.11 for assessing gaze span competency for manoeuvres are:

IF fixations in 1st and 2nd segment are ‘High’ and fixations in 3rd segment are ‘Medium’ then competency is ‘High’ (since this is the gaze span observed for experienced drivers)
IF fixations in 1st and 2nd segment are ‘Low’ and fixations in 3rd segment are ‘Medium’ then competency is ‘Low’ (since this is the gaze span is different from experienced drivers)

Using these fuzzy sets and rules, any eye gaze pattern can be distinguished between high/low competence levels.

<table>
<thead>
<tr>
<th>No. of fixations in 1st and 2nd segment</th>
<th>No. of fixations in the 3rd segment of the road</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><strong>Low (L)</strong></td>
</tr>
<tr>
<td>Low (L)</td>
<td>VeryLow_Compt.</td>
</tr>
<tr>
<td>Medium (M)</td>
<td>Medium_Compt.</td>
</tr>
</tbody>
</table>

Table 6.11: Inference rules for gaze competency evaluation using number of fixations in the 1st plus 2nd segment and 3rd segment

*Compt.: competence

By utilizing such a system that is able to evaluate gaze competency, it will eventually help flag any parts of manoeuvre the driver might not have performed competently.

Figure 6.10: Trapezoidal membership functions for the number of gaze points for: Pre-overtake in (a) the 3rd segment (b) the 1st and 2nd segment combined
During overtake in (c) the 3rd segment (d) the 1st and 2nd segment combined
Post-overtake in (e) the 3rd segment (f) the 1st and 2nd segment combined

As mentioned before, along with observing a significant difference in gaze span of the novice and experienced drivers, the other significant finding was the difference
in the fixation duration of the two groups of drivers. The fixation duration assessment rules and membership functions are presented in Appendix B.

6.5 Summary

This chapter discussed how fuzzy set theory can be used to identify competence in the tasks involved during the driving manoeuvres. The analysis sections highlighted the dissimilarity in the driving behaviours amongst novice and experienced drivers. By modelling the expert’s knowledge using fuzzy logic, rules to identify low and high level of competence for manoeuvring were defined. The fuzzy sets to evaluate competencies of particular driving tasks, which eventually lead to competency evaluation of driving manoeuvres, were also identified. In order to highlight the differences, a driving experiment was conducted to identify the empirical differences between novice and experienced drivers. Details of the driving experiment were also presented in this chapter. The results of the driving study helped refine the rules and the membership functions. The multiple factors that influence driving (i.e. variables related to driver, vehicle and environment) were presented. Along with the presentation of the multiple factors influencing driving tasks, the impact of these factors on each other was also clarified using Generalised Linear Model (GLM). The GLMs’ predictions were later utilised in creation of the membership functions for fuzzy sets.

The results from the driving experiment indicated that significant differences existed between novice and experienced driver in terms of their gaze pattern and duration, speed, stop time at the T-crossing, lane keeping and the time spent in lanes while performing the selected manoeuvres. Interestingly, no significant differences were found for the indicating before a turn. This suggests that novice drivers who participated in the study had the same judgment of distance calculation as experienced drivers. These results help identify models for competency evaluation that can differentiate low or high level of driving competence for the chosen tasks. Since driver trainers are considered to be proficient drivers, their undertaking of manoeuvres was modelled as high competence level of driving.

The competency assessments, modelled using fuzzy logic, helped identify driving abilities that are required for skilled driving. Diversions made by novice drivers
from the experienced (high competence) model of driving will flag areas where improvements need to be made in order to aid and support novice drivers’. These automated assessments combined with visualisation techniques will act as an assisting tool for the driver trainers and trainees to identify the driving competencies required and understand shortcomings on part of novice drivers.
Chapter 7

Design and Validation of the Visualisation Module

The previous chapter presented the use of fuzzy set theory to evaluate performance for the tasks performed during the driving manoeuvres. Once the areas that needed improvement have been identified (i.e. low competence) by the Intelligent Driver Training System (IDTS), the next step is to provide feedback in order to increase drivers’ understanding of the driving task and eventually enhance drivers’ performance.

One of the key aspects of driver training programs is assessment or feedback on the driving tasks. Past research findings clearly support the contention that the driver training program effects positive changes in driving attitudes and behaviours (Senserrick and Swinburne, 2001). To provide an effective feedback to the drivers, it is necessary that the massive amount of data related to the driving task is presented in an efficient and user friendly manner. Data visualisation techniques seek to overcome this problem by providing a means to analyse large sets of data. This is made possible by closely tying the end user to the data analysis process (Troy and Moller, 2004). By providing a rich set of graphical interfaces and displaying information about the driving tasks, Intelligent Driver Training System (IDTS) visualisation module is potentially able to provide empirical feedback to its users. The visualisation module will help achieve one of the aims of this research which is
to design an integrated visual interface that assists driver trainers in effectively communicating driving behaviour to their trainees. Both trainers and the trainees can potentially benefit from this visualisation module. Driver trainers will be able see driving patterns and trends that need improvement by having a holistic view of the driving tasks and this will enable the trainers to better explain to trainees the driving behaviours that need improvement. This chapter presents the design and implementation of the visualisation module of Intelligent Driver Training System (IDTS) for potential feedback.

Along with the presentation of visualisation module for IDTS, this chapter aims to validate the automated objective assessments made by IDTS with that of a driver trainers’ subjective assessment. The deployment of Intelligent Transport Systems (ITS) technologies has the potential to yield benefits to road safety. However, it is necessary that these systems are tailored to the specific safety needs of road users and that human factors knowledge and principles are incorporated into the design, deployment and evaluation of these systems. This requires evaluation of the proposed Intelligent Driver Training System (IDTS), which assists in the evaluation of driving manoeuvres.

The information presented in this chapter is as follows: Section 7.1 will discuss the benefits of data visualisation and its application in order to visualise the driving tasks in detail. Section 7.2 presents the design phase of the conversion for the data collected during driving into Extensible Markup Language (XML). It also presents the overlay of XML data on GoogleMaps for effective and integrated viewing of the selected manoeuvres. Section 7.3 discusses the method used in the validation of IDTS visualisation module. Section 7.4 presents the results of this evaluation and finally the summary is presented in section 7.5.

7.1 Monitoring and Feedback of Driving Tasks

As mentioned previously in this thesis, driver trainers are unable to assess every driving detail of their trainees while they perform the driving manoeuvres. This is mainly due to the excessive amount and complexity of information involved in driving. Driver assessment from a human perspective is a multi-task, observing complex behaviour that includes tasks such as steering, managing the throttle and
brakes, controlling the speed, lane choice, navigating and hazard detection (DiStasi et. al., 2009). Monitoring all these abilities requires excessive and complex processing on behalf of the driver trainer. This requires a need for a system that can assist the driver trainers in providing objective assessments to their trainees. Intelligent Driver Training System (IDTS) provides an effective mechanism to record the multiple factors, from driver, vehicle and environment (DVE) and segment out the information required for assessments. An effective visualisation of the driving tasks is a key factor in providing a potentially holistic feedback related to the driving manoeuvres. Data Visualisation is an emerging field that takes advantage of data processing techniques and rich computer graphics to present useful information from collected data.

7.1.1 Data Visualisation

This data visualisation provides distinct advantages over traditional data analysis techniques. The ability to analyse large data sets is one such advantage. Traditional tools for analysing data such as spreadsheets, ad hoc queries, statistical analysis and summaries, are no longer sufficient for the volumes of networked data that businesses want to analyse (Eick et al, Visualizing Corporate Data). Statistical analysis, though powerful, is a reduction technique and thus, may obscure important information. Data visualisation techniques seek to provide the means to analyse large sets of data.

Recently, software and hardware technology has improved to a point where the practical use of applications with interactive three-dimensional graphics is a viable prospect. Data visualisation software takes advantage of these advances by providing users a rich set of graphical displays, enabling users to quickly step through various pictorial views of the data (Youngworth, 1998). Visualisation simply means presenting information in pictorial form and using human recognition capabilities to detect patterns (Eick and Fyock, 1996). Visualisation techniques often focus on information that is abstract, which means that many interesting classes of information have no natural or obvious physical representations. Analysts have used simple two-dimensional graphs, charts and other visual aids to interpret and convey data information for some time now. However, the data visualisation techniques presented in this thesis differ from previously mentioned applications because they
focus on the ability to analyse multidimensional data, provide the user an interactive interface, and provide the ability to access the actual data underlying the visual representations using a "drill down" process. The visualisations represent the processed data in a pictorial way that better highlights the trends, patterns, and anomalies. Other data visualisation software allows the user to define characteristics of the data in order to determine an analysis algorithm.

In this thesis, data visualisation is defined as the process of applying automation algorithm and a discovery process to the driving data sets in an effort to present the processed information from the data. This data visualisation module for potential feedback also provides interactive user interfaces that allow users to continuously manipulate data parameters, adding great flexibility to the analysis process. It utilizes the techniques identified by Troy and Moller (2004) such as interactive multiple views, colour encoding of data and multiple overlays to improve the effectiveness of the driving tasks’ visualisation.

### 7.1.2 Feedback Effectiveness

It is well known that drivers, who are exposed to driver training, show an increase in behaviours that can enhance their situational awareness and also show increase in favourable driving behaviours (GuyWalker et. al., 2008 and Jose and Mayora, 2008). Before feedback information can be identified, irrelevant information must be removed without eliminating information that is relevant to safety. Second, the information needed to provide driver feedback on even simple tasks such as lane keeping, must be compiled from various sources and then combined in a manner that allows accurate coherent feedback information. The difficulty of this task is only amplified in the case of more complex driving behaviours such as overtaking or making a left hand turn.

One of the key aspects of driver training programs is to provide assessment or feedback on the driving tasks. This can be either self assessment or assessment from another group or individual. Extensive research has revealed that it is not so much the lack of basic driving skills that cause the crashes, but higher order skills. These higher order skills deal with risk perception, situational awareness, risk acceptance, self assessment and motivation to drive safely (Jose and Mayora, 2008). Novice
drivers misinterpret the situation (dismissing one of the crucial tasks in driving) and show inefficient visual search. Self assessment tools such as questionnaires, scales and evaluations made by instructors or driver trainers help to address the gaps in novice drivers’ driving abilities. By comparing novice drivers’ performance of a manoeuvre with that of experienced drivers’, makes it easy to pinpoint the flaws (if present) in novice drivers’ behaviour.

Efforts have been made in the past to measure aspects such as driver distraction or risk perception for example, researchers Klauer et al. (2006), studied driver distraction offline by manual analysis of video recordings. This was a cumbersome and time consuming process. Furthermore, parents have an important role in increasing the amount of supervised driving the novice drivers undertake, which seems to reduce subsequent risky behaviour (Klauer et al., 2006). Thus, the goal of training should be to create safer drivers, which involves instilling young drivers with a sense of their own limitations and understanding of the risks and its causes.

McKenna (2006, p.6) wrote “If it is considered that drivers would benefit from feedback and education on issues such as close following, general driving violations, fatigue and hazard perception, then mechanisms need to be put in place”. Until now many driver feedback programs have been designed, each trying to cover as many aspects of driving as possible (Hong et. al., 2006; Pollatsek et. al., 2006 and Vigil System). However, to our knowledge, there is no integrated automated feedback system that allows the driver and driver trainers to effectively and efficiently observe and measure all of the variables involved in driving (i.e. Driver, Vehicle and Environment also known as DVE).

IDTS visualisation module has the potential to provide an integrated feedback solution by combining the benefits of multiple sensors such as GPS, accelerometers, cameras, vehicle information, driver’s head/eye data and geographical data. The details of the design and the working of this visualisation module are presented in the following sections.
CHAPTER 7. DESIGN & VALIDATION OF VISUALISATION MODULE

7.2 Information of Driving Tasks Conversion to XML

One of the main components of the visualisation module is the overlay of driving data on GoogleMaps. Google Maps have become the most widely used web mapping service application and technology provided by Google, that powers many map-based services, including Google Maps, Google Transit, and maps embedded on third-party websites via the free Google Maps API (Massengill, 2010). GoogleMaps control allows readability and parsing of Extensible Markup Language (XML) data files using JavaScript. In-order to present the processed driving information on the map, it is necessary to convert that information in XML data format since GoogleMaps only supports XML type data.

XML is a specification for storing and exchanging data that the World Wide Web Consortium (W3C) created in 1996 to standardise information delivery across the Internet (W3C, 2008). XML is similar to HTML in such a way that XML uses tags and attributes to define data in the same way that HTML uses tags to define formatting. However, instead of having a fixed set of tags, as HTML has, XML lets the creator define the tags its XML streams use. Therefore, custom tags can be used to make content self evident. XML is a technology for marking up structured data so that any software with an XML parser can understand and use its content. XML is intelligible to both humans and machines. Any application can conceivably process XML data (W3C, 2008). Therefore, XML is ideal for data exchange. XML is simple because it is modular and the author and provider can design their own document type using XML. Figure 7.1 below, presents the conversion of the automated segmentation of driving data into XML format.
The Intelligent Driver Training System (IDTS) processes and segments out the selected manoeuvres and their parameters (i.e. average speed, excessive force, gaze direction, distances and indicator usage) in an automated manner. This processed information is later converted into XML script for viewing on GoogleMaps. The prototype of this visualisation module is presented in the following section.

### 7.2.1 Visualisation of Driving Data

Multimedia technology has changed the visualisation of spatial data. The map, the traditional presentation of spatial data, is complemented by other media such as pictures, animation, sound and video. Each of these additional media has particular
abilities to communicate information. The graphical interfaces for the visualisation module of driving has to present information in a way that people without great knowledge of the subject (i.e. driving assessment) can perceive and understand that subject.

According to Youngsmith (1998), data visualisation software has three features that make it possible to interpret large stores of data:

- Specialised views that can display large quantities of data on a single page.
- The ability to instantly highlight exceptions in the data.
- The ability to display slices of data as visual patterns.

All of these software characteristics are present in the Intelligent Driver Training System (IDTS) visualisation module. As mentioned before, using Google maps API, it is possible to load/overlay the XML data related to the driving task on Google maps. Figure 7.2 below illustrates the interaction between the different technologies and their sub-modules in the presentation of a potentially effective feedback for the driving manoeuvres. Once the XML file for the driving tasks has been generated by IDTS (shown in Figure 7.1), it is then loaded by the GoogleMaps control. The data in the XML file is managed using the timestamps of the driving tasks conducted during the driving experiment. To synchronize the maps control with the controls in MATLAB, that contains the complete graphical representation of the driving, images of the road for a given time and the slider control for viewing data related to a certain time, a shared memory location is used.
The following section will present the prototype and explain in detail the interfaces involved in providing potential feedback for the driving manoeuvres.

### 7.2.2 Integrated Visualisation using Mapping

We have argued that the key problems remaining in road safety are driver-centred and require a driver-centred intervention. Providing immediate and aggregate feedback to the drivers regarding their driving performance is necessary to address this key problem.

The Intelligent Driver Training System (IDTS) visualisation/potential feedback solution combines the benefits of multiple sensors such as GPS, accelerometers, cameras, vehicle information, driver’s head/eye data and geographical data and interactive interfaces. This was accomplished by processing data from the driving task using complex algorithms, to retrieve information such as but not limited to; following distance during particular manoeuvres, indicator distance before manoeuvres, average speed during manoeuvres, excessive braking or accelerations, driver gaze depth and orientation etc. All these information synchronously plotted on an interactive map definitely complements the effectiveness of the visualisation system.
Presenting an integrated visualisation of the driving scenario is a significant part of providing feedback to the driver. Since the end users of IDTS are driver trainers and trainees, it is necessary that data from the complete driving scenario (recorded from multiple sensors) and low competency situations are represented in a way that is easy to comprehend. Hence, it will be easy for the driver trainers to highlight and explain specific scenarios to the driver. An integrated graphical mapping of the data collected during the performed driving tasks, ensures that the data collected and processed is not just organised information rather actionable intelligence.

Figure 7.3 below shows a part of the integrated visualisation module. The X axis shows the distance travelled by the vehicle. Y axis from 0 till ‘100’ shows driver’s speed (km/h) and scaled down average gaze depth (in metres). Further up on Y axis, the points highlighted are indicators switching on and off, points where brakes were applied, locations where the vehicle turned, points where lanes were changed and if these lane changes were for an overtake manoeuvre, excessive acceleration or deceleration points and locations at which the driver checked rear or side mirrors. The three manoeuvres that are segmented out from the driving scenario by this system are identified by their labels. Another notable point is that, if these manoeuvres were performed in a low competent manner, the identification labels of these manoeuvres will change colour from blue to red (as shown by the legend in Figure 7.3). Using such a graphical interface, driver trainers and trainees will be able to empirically check multiple driving parameters for a certain time ‘t’ in a synchronous manner.

But the graph presented in Figure 7.3 does not allow the ability to view road parameters (i.e. the location of an intersection light, location of a roundabout etc). In order to handle this issue, IDTS provides a map in the feedback module. Since all information from the driving scenario (acquired from DVE) is recorded in a synchronous manner, it is possible to display the vehicle position along with the driver gaze points on a map (i.e. GoogleMap) for any given time. Along with this, by clicking any vehicle trajectory point on the map, the framework is able to display its corresponding location on the graphical representation of the driving scenario (i.e. Figure 7.3). The map also flags the manoeuvres that were not performed in a
competent manner. Upon clicking the flags, the map will display the reason IDTS considered the manoeuvre to be of low competence level (which is assessed using fuzzy rules).

One of these flag is visible in the Google map display (i.e. label number 2) of Figure 7.4. As it is apparent, the integrated visualisation module for potential feedback in Figure 7.4 has four display panels. Description of each display is as follows:

1. The slider control select certain time ‘t’ of interest and this is the main controller. Display 2, 3 and 4 present the driving scenario for the slider selected time.

2. The interactive map (i.e. GoogleMap) that displays the recorded vehicle trajectory (in red line).
   - The position of the vehicle (i.e. the car icon)
   - The drivers’ gaze direction and depth (in green dots and lines)
   - The start (in yellow star) and end (in pink star) positions of the indicator.
   - Red dots to mark excessive accelerations or decelerations.
Figure 7.3: A graphical representation of complete driving scenario
Figure 7.4: The integrated visualisation module with four displays for potential feedback.
• The flags display if a manoeuvre is not performed in a competent manner. As stated above, the manoeuvres included are turning, lane change, overtake and stopping. Upon clicking the flag, a table appears (show in display 2) at the bottom of the map. This table displays the manoeuvre and the competence level of each task (shown by variable ‘FuzzScr’) within that manoeuvre. Competence is normalized between 0 and 1 with 1 being the lowest competence.

3 The camera image (displaying the road ahead) overlaid with the driver's gaze (blue box) for a selected time.

4 The graphical representation of the complete driving scenario. The solid blue vertical line displays the position of car based on the slider selected time. The vertical red dotted line corresponds to the point clicked on the vehicle trajectory displayed in Google map (i.e. display 2). This allows the driver trainers to view position of road landmarks (i.e. traffic lights, crossings, roundabouts etc.) on the driving scenario’s graphical representation (display 4). This helps to assess behaviour such as did the driver change lane while crossing the traffic light? Along with this, the selected manoeuvres’ competence is displayed by a change in colour of their detected location (shown in Figure 7.3 ‘legend manoeuvre competence’).

This effective and dynamic visualisation will help driver trainers to better empirically assess (both weaknesses and strengths) the driving tasks. Along with this, integrated visualisation will allow the drivers to self assess the manoeuvres they have undertaken.

7.3 Validation of the IDTS

Currently it is difficult to come to a definite conclusion about whether a given ITS application for improving driver behaviour or performance will, or will not, enhance safety (Regan et. al, 2001). The reason for this inconclusive benefit to road safety is that crash studies, which are the traditional measure of change in road safety, are not appropriate for deriving safety information in the ITS context (Regan et. al, 2001). ITS technologies have never been deployed on a scale large enough over a long enough period of time in traffic for the crash numbers to be a reliable indicator
of a change in safety (Regan et. al, 2001). Therefore, the potential safety benefits of
training systems have yet to be established as the research findings relating to this
class of system are varied and contradictory. Validation is one of the processes that
will confirm the benefits of training systems. McDowall (2005, p.39) mentions that
“validation is a journey and not a single event in a systems life cycle. Ongoing
revalidation of a system is required until the system ceases operation”.

Behavioural adaptation to Intelligent Transport Systems (ITS) through acceptance
of the systems is an important human factor issue identified in the literature; albeit
one that has received little investigation (Regan, 2001). A willingness to install and
use such a system is important since it will ultimately dictate whether the system can
be successfully adopted within driver training organisations. Output data from the
system will be assessed for its usefulness as an evaluation tool. This section validates
the findings and objective evaluations of IDTS visualisation module with that of a
driver trainers’ subjective assessment.

7.3.1 Validation Method

The evaluation of training obviously requires the collection of data on performance
and the subsequent analysis of this data. This data collection was conducted using
the experimental setup presented in Chapter 6. As mentioned in section 6.3
(Driving Experiment), every participant repeated each lap of the test track ten times.
The data collected during the last three laps were used in the validation of the
assessments. The comparison of driving manoeuvre evaluations was made between:

- Driver trainer’s recordings of the subjective evaluations during the laps and
- Intelligent Driver Training System (IDTS) recorded and processed data,
  resulting in empirical evaluation.

The output of IDTS, which was the evaluation of the driving manoeuvres
(objective), was matched with recorded evaluations by the driver trainer (subjective).
These evaluations were presented to the driver trainers and both evaluations were
matched to validate the results.
A sample assessment form used by the driver trainers to evaluate the driving manoeuvres for this driving experiment is given below (Figures 7.5 and 7.6). The driver trainer divided the driving experiment (detailed in section 6.3 ‘Driving experiment’) into loops and phases. They are shown in Table 7.1.

<table>
<thead>
<tr>
<th>Loop 1</th>
<th>Loop 2</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Phase 1</strong> -&gt; Left on T-crossing</td>
<td><strong>Phase 1</strong> -&gt; Second Overtake</td>
</tr>
<tr>
<td><strong>Phase 3</strong> -&gt; Curve</td>
<td><strong>Phase 2</strong> -&gt; Curve</td>
</tr>
<tr>
<td><strong>Phase 4</strong> -&gt; Overtake</td>
<td><strong>Phase 4</strong> -&gt; Left Turn</td>
</tr>
</tbody>
</table>

Table 7.1: The two loop during the experiment and their division into multiple phases (manoeuvres) as arranged by the driver trainer.

In figures 7.5 and 7.6, the numbers 1 till 10 describe the 10 laps that each participant had to complete. The tasks that each phase contained are presented in tabular form (i.e. Phase 1, 2, 3 and 4) in Figures 7.5 and 7.6. The driver trainer confirmed they performed each task in the respective phase and wrote comments if the tasks performed were at a low competency based on the trainer’s subjective assessment.
Figure 7.5: Part 1 of the driver trainer's assessment form for an inexperienced driver
As illustrated in Figures 7.5 and 7.6, the subjective assessments of the tasks whilst driving include turn on T-crossing, left turn, curve, lane change, overtake and stop.
The next section deals with checking the less competent driving situations as identified by the driver trainer, with that of the IDTS manoeuvre assessment.

## 7.4 Results of IDTS Evaluation

The main reason for validating this system is an attempt to maintain the accuracy and integrity of the data (assessments) generated by the system. This section will present the description of the driver trainer’s subjective evaluation side by side with the Intelligent Driver Training System (IDTS) automated empirical evaluation for the same driving tasks. This validation process was conducted with assistance from a driver trainer.

The figures 7.5 and 7.6 present the subjective evaluations of the driver trainer for an inexperienced driver (novice participant ID 2 in driving experiment). While, Figure 7.7 presents the automated assessment for the same inexperienced person using IDTS.

![Image of the graphical interface of IDTS presenting the driving performance](image)

**Figure 7.7:** The graphical interface of IDTS presenting the driving performance.
Figure 7.7 displays the two interfaces out of the four possible interfaces for visualisation of the driving tasks (see section 7.2.2 for the complete graphical user interface). Although this system provides automated assessment and interactive feedback for all turns on T-crossing, left turns, curves, lane changes, overtakes and stops, this section will provide the result of validation using turns and overtakes.

It is apparent from the driver trainer’s comments, that during overtakes (i.e. loop1-phase4 and loop2-phase1) the inexperienced driver was following the vehicle that he/she was trying to overtake, too closely. This is a subjective observation from the driver trainer and should be picked up by the automated assessment of IDTS. Figure 7.7, highlights this finding (Label 2 and 4) by colouring the flags as red and orange indicating that some driving tasks during the overtake manoeuvre might have been performed in a less competent manner.

Upon clicking the red flag (for overtake1), a table drops down (shown in Label 2) which presents all the tasks that were monitored using the rule based assessment. A competence assessment score was also calculated based on the evaluating rules. It can be observed that the competence score for the overtake manoeuvre’s, following distance task, is calculated to be 0.597, which is ‘low competence’ based on the assessment scale (see Figure 6.8- The competence assessment’s fuzzy membership functions). The same low competence notion can be grasped from Figure 7.7-Label 4 (graphical representation of the driving scenario), which shows the overtake manoeuvres in red indicating low competency level.

For overtake2, the competency assessment score as calculated by IDTS was 0.419. This score made the second overtake as medium competence (see Figure 6.7- The competence assessment’s fuzzy membership functions). Both of these assessments were confirmed and validated by the driver trainer. Along with this, the turn manoeuvre (i.e. loop2-phase2) in the driver trainer’s subjective assessment is safely undertaken. The same assessment is measured by the IDTS, in the form of blue flag (Figure 7.7) indicating high competence/proficiency. The same validation was conducted for multiple driving tasks. The driver trainers were satisfied with the automated assessment of manoeuvres using IDTS.
A tabular form for the assessments/comments, for the participants of driving experiment, as made by driver trainers and the IDTS system is presented below in table 7.2.
<table>
<thead>
<tr>
<th>ID</th>
<th>Driver Trainer</th>
<th>Intelligent Driver Training System</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Manoeuvre</td>
<td>Fuzzy Score/Competence</td>
</tr>
<tr>
<td>NOV2</td>
<td>Overtake 1</td>
<td>Too close following distance</td>
</tr>
<tr>
<td></td>
<td>Overtake 2</td>
<td>Close following distance</td>
</tr>
<tr>
<td></td>
<td>Curves</td>
<td>Maintained curve radius</td>
</tr>
<tr>
<td>NOV3</td>
<td>Curve 1</td>
<td>Poor corner vision</td>
</tr>
<tr>
<td></td>
<td>Curve 2</td>
<td>Poor corner vision (very)</td>
</tr>
<tr>
<td></td>
<td>Overtake 1</td>
<td>Close following</td>
</tr>
<tr>
<td></td>
<td>Overtake 1</td>
<td>No comment</td>
</tr>
<tr>
<td></td>
<td>Overtake 2</td>
<td>No comment</td>
</tr>
<tr>
<td></td>
<td>Overtake 1</td>
<td>Too close to left lane</td>
</tr>
<tr>
<td></td>
<td>Overtake 2</td>
<td>Too close to left lane</td>
</tr>
<tr>
<td>NOV1</td>
<td>T-cross</td>
<td>Looked across properly</td>
</tr>
<tr>
<td></td>
<td>Overtake 1</td>
<td>No comment</td>
</tr>
<tr>
<td></td>
<td>Overtake 1</td>
<td>Good lane positioning</td>
</tr>
<tr>
<td></td>
<td>Overtake 2</td>
<td>Good lane positioning</td>
</tr>
<tr>
<td>EXP3</td>
<td>Turn 1</td>
<td>No comment</td>
</tr>
</tbody>
</table>

Table 7.2: Comparison of manoeuvre assessments by driver trainer (subjective) and the Intelligent Driver Training System (objective)
In Table 7.2., NOV1 till NOV3 represent novice drivers 1, 2 and 3 in the driving experiment whereas EXP3 stands for the experienced driver 3. This table highlights the comments from driver trainers as they subjectively evaluated the different drivers performing the selected manoeuvres. Furthermore, the assessments for the same manoeuvres and tasks by IDTS are presented in parallel. It can be observed, that IDTS objective evaluations, utilising fuzzy set theory, are very similar to the driver trainer’s subjective assessments. In addition, since driver trainers cannot completely assess all the variables involved in driving due to increased mental workload, some medium and low competent performed manoeuvres were picked up by the IDTS while they were not detected by driver trainers.

Another notable point is that in the assessment by driver trainer for the T-Crossing, it was mentioned that the novice driver failed to stop three times. This driving flaw is not picked up by IDTS since IDTS does not possess the ability to automatically detect stop signs. The evaluation of the ‘stop time’ at T-crossings is done manually by selecting the location that has the stop sign and later computing the amount of time a driver stopped at that selected location. The automated detection of stop times at T junctions can be encompassed in the future version of IDTS.

Even though the driver trainers validated the Intelligent Driver Training System (IDTS) visualisation module, the potential safety benefits of such training systems have yet to be established as the research findings relating to this class of system are varied and contradictory. The on-road research studies reviewed and implemented in this thesis suggests that these systems have the potential to yield results that can be used by novice drivers to better detect and respond to traffic hazards.

### 7.5 Summary

Research suggests that training does improve the driving performance required for road safety. Senserrick et. al. (2001) found that their training program resulted in important road safety messages being relayed and adopted in a relatively short time period. They suggest that researchers and others involved in the field of road safety should consider the potential benefits of training (Senserrick and Swinburne, 2001).
Young drivers particularly, have a high crash liability relative to those with a few years of driving experience. This suggests that experience offers skills that enable experienced drivers to avoid crashes. Teaching these skills to young drivers through effective driver training will improve young driver crash rates. The Intelligent Driver Training System (IDTS) feedback module presented in this chapter provides simple interactivity to allow an increased level of detail on demand.

This chapter presented the design and interface of the visualisation module that was used by trainers and trainees to better understand the driving tasks and provide feedback. The visualisation module consists of methods to convert the driving scenario data into XML storage file. This data file can be read easily using GoogleMaps displaying the competencies associated with the detected manoeuvres. Furthermore, the multiple views of the driving tasks were presented which signal the locations of the road on which the driver was focused, a holistic view of the driving scenario and a slider control to select any location of interest.

Feedback on the executed driving manoeuvres, highlighting both strengths and weaknesses of the driver will act as an effective measure to improve driving skills. Thus, driver training remains an important road safety intervention to improve driving performance and abilities, particularly amongst young people. Eventually both drivers and driver trainers will be able to assess the driving performance using this feedback system. Thus raising young drivers’ awareness of factors that contribute to crashes and potential risks when driving.

In addition to designing a visualisation module for providing feedback about the driving tasks, evaluation of such feedback system is deemed necessary. The proposed training system’s (IDTS) evaluation of the driving manoeuvres was validated by the driver trainers’ subjective assessment. Since the end users of this training system are drivers and their trainers. It is of the utmost importance that the users (i.e. driver trainers) of this system find it user friendly and corresponding to their assessments. This system is not intended to replace the driver trainers instead; it is an assistance tool for driver trainers to empirically assess the manoeuvres undertaken by the trainee drivers. This system helps to track and evaluate performance that the driver trainers might have missed due to information
overload. Trainers can also use the empirical evaluation of the driving tasks to countercheck any task they might have overlooked.
Chapter 8

Conclusion

This thesis has extended and integrated multidisciplinary research into a methodological framework for the design and validation of a performance assessment system named Intelligent Driver Training System (IDTS). This chapter summarises all the work presented in the previous chapters.

This chapter begins with the presentation of research questions and an overview of the research approach. Section 8.2 presents the summarised outcomes for each of the previous chapters. It is followed by section 8.3 which evaluates the results of this research, identifying contributions to the multiple fields involved in this study, specifically road safety research, driving behaviour and human machine interface. Section 8.4 covers the limitations of modelling driving manoeuvres and finally Section 8.5 concludes with an outline for future work that should be addressed to implement an effective driver training program for identifying low competent manoeuvring.

8.1 Original Aim and Research Questions

The aim of this research was to develop and evaluate an in-vehicle assessment tool that helps to assess objectively driving competencies. The main research questions addressed in this thesis and presented in Chapter 1 are:
• Do differences exist between novice and experienced drivers when they attempt certain driving manoeuvres?
• What are those differences in the driving context?
• Can these differences be evaluated using expert’s knowledge (by fuzzy rules) and assessed as high or low competence levels?
• Can an interactive interface be designed that presents the driving task’s assessments in an effective manner?

Research Approach
As already mentioned, a framework that has the ability to identify and assess driving differences in novice and experience drivers and has the potential to provide feedback on the strengths and weaknesses of a driver is needed. The proposed research identified the multiple parameters and recorded these parameters from Driver, Vehicle and Environment (DVE) through cameras, laser scanners and multipurpose sensors. Some of these variables included following distance, frequency of mirror checks, gaze depth and scan area, distance with respect to lanes and excessive acceleration or braking. These variables were recorded for many manoeuvres (i.e. turns, overtake, lane change) that constitute a driving task.

To address these differences in novice and experienced drivers in the driving context, a driving experiment was conducted on a closed loop track. Both groups of drivers performed the selected manoeuvres under the supervision of driver trainers and the driving tasks’ recording system. This experiment recording system was also able to segment out the selected manoeuvres and the associated variables recorded during the performed driving tasks. This driving experiment helped to objectively identify the manoeuvring differences in novice and experienced drivers.

These differences were modelled using rule based assessments. These assessments were based on the differences identified from the driving experiment. Driver trainers were consulted to confirm the devised assessments. In-order to present these assessments and feedback to trainees and their trainers, an interactive user interface highlighting the strengths and weakness of the driver was designed.
Lastly, the validation of the proposed system’s assessment was made by comparing it to the subjective assessments of the driver trainers for particular manoeuvres. Potential benefit of such a framework includes identifying and sharpening driving abilities that are required for skilled driving.

8.2 Summary

The research presented in this thesis emphasised the need and usefulness for an Intelligent Driver Training System (IDTS). The focus was on designing and implementing a system that can comprehensively determine the competence level of driving manoeuvres and provide feedback on the driving tasks in an intuitive manner. To the best of our knowledge, advanced driver assistance systems have never been comprehensively used in a driver training context to assess driver performance nor driving competence levels. One of the important aspects of the Graduated Driver Licensing (GDL) program is to enable less experienced drivers progressively gain driving experience. GDL addresses the fact that both instructors and drivers should have an opportunity to establish and nurture the driver’s productive patterns of thinking and it should promote higher levels of awareness around their own learning and driving ability. The proposed IDTS is helpful in assessing objectively the Graduated Driver Licensing (GDL) program by:

- Dealing with the aspect of driving for less experienced drivers.
- Logging and diagnosing driving behaviour during training.
- Providing a framework enabling instructors and learners to discuss the learner’s performance.

A summary of each chapter from this thesis, justifying the need and workings of such a system is provided below.

Chapter 1 - Introduction

This chapter highlighted driver inexperience as one of the main factor contributing to road crashes amongst young drivers (ECMT, 2006). The burden of crashes was counted not only in lives and permanent injuries but also as a cost to the society. It mentioned that even though road fatalities have decreased in the past decade, the social cost of crashes has increased considerably (Queensland Transport, 2009).
Road crashes were also found to be the single biggest killer of 15-24 years old in industrialized countries (ECMT, 2006). Young drivers’ high involvement in road crashes is often attributed to lack of driving skills. This high crash risk has led to calls for more and better training of novice drivers.

One of the interventions aimed to minimise young drivers’ crash risk is driver education. The aim of this thesis was to identify the need; the creation and evaluation of a tool that can help objectively assess driving competencies. Keeping this aim in perspective, the main research questions were identified. A high level approach which enables answering the research questions and the contributions of the thesis were presented.

Chapter 2 - Theory of Driver Education

In this chapter, theories on driver education were surveyed and the limitations of the current driver education programs were presented. A fundamental approach to solving engineering related public problem (i.e. Engineering, Enforcement, Education and Engagement) was presented.

The main goal of driver education programs, in light of Graduate Driver Licensing (GDL), was reviewed and the limitation of skill based training programs was highlighted. This chapter also discussed the driving task performance and skill acquisition in detail. Research indicates that three elements are essential for the development of expertise with a complex skill such as driving (Keating, 2007; Keating & Halpern-Felsher, 2008). They are

1) focused practice and rehearsal of the skills to be learned (Ericsson, 2002; Ericsson, 2005; Ericsson, 2006)
2) devotion of time to the task (Ericsson & Charness, 1999; Ericsson, 2002; Ericsson, 2005; Ericsson, 2006). Mastery of a complex set of skills, such as those needed to drive safely, develops gradually with experience gained over a significant period of time and
3) automaticity (Keating, 2007) which relates to attention and appropriate responses becoming “automatic,” requiring little or no conscious attention with sufficient experience. Hence, an experienced driver will generally respond to subtle external
events that warn of possible risk, while inexperienced drivers are less likely to do so (Lee et al., 2008; Pradhan et al., 2005).

This chapter emphasised the need for a standardised driver training program. Understanding how the acquisition of driving expertise evolve (i.e. novice to experienced drivers) may shed light on approaches and policies that could enhance or accelerate this process.

**Chapter 3 - Advanced Driver Assistance System (ADAS)**

This chapter reviewed various technologies and techniques that have been applied to solve issues surrounding the field of Intelligent Transportation Systems (ITS).

Together with this, it provided the different safety systems that are monitoring parameters related to driver, vehicle and environment. It mentioned the limitation of existing Advanced Driver Assistance Systems (ADAS) in the context of comprehensive driving assessment. This chapter discussed the need of an intelligent driver training system for assessing drivers in light of current solutions and technological equipment provided for enhancing road safety. This chapter also underscored the benefits of fusing multiple driving parameters acquired from Driver, Vehicle and Environment (DVE) to assess driving manoeuvres in a comprehensive manner.

**Chapter 4 - Performance Assessment**

This chapter highlighted the gap in terms of assessing different driver behaviours as safe or dangerous. This chapter introduced how driver behaviour has been modelled in the literature, with emphasis on the difference of modelling inexperienced and experienced driving manoeuvres.

Differences between driving behaviour and performance from previous literature was also identified and together, a definition of performance was defined in this chapter that enabled the modelling of competency (low or high) to be used in the thesis. This chapter underscored the difficulty in modelling driver behaviour by listing the uncertainties involved in a driving task and the difficulties involved in modelling uncertainty. It also presented the criteria for driver behaviour modelling that can identify performance ranging from highly competent to less competent in
light of the competency definition introduced in this chapter. In this thesis, expert drivers’ (i.e. driver trainers) assessments and their driving performance were considered of high competence since they are considered to be proficient drivers. Based on the behaviour modelling criteria, this chapter compared multiple mathematical modelling techniques and found fuzzy set theory to be the most suitable.

**Chapter 5 - Design Of Intelligent Driver Training System (IDTS)**

Based on the findings from the previous chapters, this chapter presented a detailed architecture and a prototype of the driver training system that will aid the driver trainers in judging a manoeuvre’s competence. This chapter presented the proposed Intelligent Driver Training System (IDTS) that provides a computational model for performance assessment in relation with the driving tasks performed during a particular manoeuvre.

A detailed discussion related to the three main modules of this IDTS system (i.e. data registration, manoeuvre identification and assessment/feedback) was presented. In the section related to data registration module, multiple in-vehicle sensors and their synchronisation process was presented. In the section related to manoeuvre identification module, different algorithms and techniques were implemented to automatically segment out multiple manoeuvres (i.e. turn, curve, lane change, overtake etc.). The section related to assessment/potential feedback presented the method in which IDTS is able to combine multiple tasks to assess a simple manoeuvre and later combine multiple manoeuvres to assess a more complex manoeuvre. This section also presented the rules that the driver trainers’ use to assess the competency for undertaking particular manoeuvres which is also used by IDTS to assess the same manoeuvres. A brief overview of the visualisation module was also presented which consisted of visual representation of the driving tasks for viewing and communicating driving behaviour to its users.

**Chapter 6 - Developing a safe performance protocol**

This chapter deals with the problem, which is characterized by uncertainty, subjectivity, imprecision and ambiguity, to actually understand what a less
competent driving situation is? And once it defines a model that can handle driving uncertainties to evaluate performance, it tries to model the difference between high and low competence levels for driving manoeuvres.

As mentioned previously, fuzzy set theory was identified to solve the issue surrounding the uncertainty of driving behaviours. The aim of this model (fuzzy logic) was to identify the distinction between low and high competence levels in driving manoeuvres. This chapter discussed how fuzzy logic was utilised for performance assessment. The primary strength of a fuzzy approach is, it is applicable to model human knowledge and the decision making process using rule based approach. For this thesis, the rules were initially designed with the help of expert knowledge (i.e. driver trainers). Later, in order to fine tune these rules and the parameters that define these rules, a driving experiment was conducted to identify the empirical differences between novice and experienced drivers. The details of the driving experiment, involving both young and experienced drivers, were also presented in this chapter. Results from the driving experiment highlighted the differences between young and experienced drivers’ performance during manoeuvres. These differences were helpful in refining the fuzzy membership functions and rules that govern the assessments of the driving tasks.

Chapter 7 – Design and Validation of Visualisation Module

One of the key aspects of driver training programs is assessment and feedback on the driving related tasks. This chapter presented the design and working of the visualisation module of Intelligent Driver Training System (IDTS) that has the potential to provide feedback. This chapter also validated the objective evaluation of IDTS, presented using the assessment module, with that of a driver trainers’ subjective assessment.

This chapter began by introducing the importance and effectiveness of information visualisation and feedback for training. It later presented in detail the multiple interfaces and the information exchange between the interfaces that is required to visualise an integrated driving scenario. It also demonstrated how the driving task related information is converted into XML, later to be overlaid on GoogleMaps for visualisation. The synchronisation of all the interfaces, displaying parameters related
to DVE, is also presented. The assessment interfaces utilises multiple methods for improved visualisation of the driving scenario.

Just like any other system, the validation of Intelligent Driver Training System (IDTS) was a key factor depicting the usefulness of this system. The comparison of driving manoeuvre evaluations was made between two driver trainer’s recordings of the subjective evaluations during the laps and IDTS recorded and processed data, resulting in an empirical evaluation. The results of the validation of the manoeuvres are presented in this chapter.

8.3 Thesis Outcomes

This section will highlight the thesis outcomes in light of the research questions identified in Chapter 1.

8.3.1 Thesis Contribution

The research presented in this PhD thesis is multidisciplinary and contributed to the knowledge of many different fields. The contributions to the different disciplines are provided below:

- Road Safety
  Crash statistics show that inexperience and age are one of the major contributing factors to road crashes. This research objectively identified the driving difference amongst the recorded variables for novice and experienced drivers. It further highlighted the relationship between the differences (i.e. how change in one variable affects other variables). It also emphasised that currently driver training is based on subjective evaluation by the driver trainer. To solve this issue, the IDTS system that provides the methodology to objectively evaluate drivers was presented.

- Computer Science
  The first contribution of this thesis to the field of computer science is by using fuzzy logic to evaluate driving manoeuvres and the tasks involved in performing them. The second contribution is estimating drivers’ gaze depth (in metres) using perspective projection algorithm that exploits the road parameters (i.e. actual
distance between lane markings (in metres), distance between lane markings on the image of the road acquired (in pixels) and horizon point on the image of the road).

The final contribution is the automated segmentation of the selected driving manoeuvres (i.e. turn, overtake and lane change) from the complete driving scenario. Along with the segmentation of manoeuvres, each manoeuvre is further subdivided into three parts namely; pre-manoeuvre, manoeuvre and post-manoeuvre. This helps to objectively assess the driver performance not just during manoeuvre but even at the approach and end of a particular manoeuvre.

**Driver Performance Assessment Modelling**

A comprehensive assessment modelling of all selected driving manoeuvres was presented in this thesis. The performance assessment modelling contained two parts. Firstly, driving manoeuvres were identified using classifiers in which basic behaviours were defined. These basic behaviours were combined to create more complex behaviours and later assessed. For example, an “overtaking” behaviour was built on “lane change” behaviours.

Secondly, the assessment modelling of the detected manoeuvres was based on fuzzy set theory. Other mathematical models to assess driving behaviours were also introduced. Based on these assessments, driver trainers were able to effectively evaluate strengths and weaknesses of drivers.

**Visual Feedback In Driver Training**

This research also presented a rich graphical user interface that has the potential for providing feedback to both drivers and their trainers. This interactive interface along with the graphical representation of the complete driving task also featured a map with vehicle trajectory and driving activities performed. The competency assessments for the selected manoeuvres were overlayed on the map. An integrated graphical mapping of the data collected during the driving made it certain that the data collected and processed was not just organised information rather actionable intelligence.
8.4 Limitations

It has to be noted that even though the experiment and the model created from the results of the experiment was conducted in a real world environment; the experiment was conducted with controlled parameters (i.e. start and stop points of the experiment, speed of the car being overtaken, same track used). On one hand, it was necessary to have the controlled parameters to identify particular patterns of behaviour (repetitive measure) on part of an individual (i.e. experienced or novice). However, by conducting a driving task on open roads should identify more behaviours differentiating novice and experienced drivers.

Secondly, a relatively small number of participants were used in this experiment. This is statistically sufficient to determine the difference between novice and experienced drivers but more participants will be needed to test the reliability and robustness of the system. In particular, male participants were over-represented in the samples used in this study. While the likely impact of such bias is unclear, it still represents a potential limitation. Another limitation was having participants who had a driving licence for less than 2 years and less than 1 year of on-road driving experience. Research suggests that the young drivers’ crash rates drop significantly after 1 year of driving; therefore the experience level of the young drivers could be a possible limitation.

Thirdly, the use of the Garmin GPS that was a part of the Vigil System did not provide sub-meter precision. Even though IDTS mostly utilizes GPS data for turn detection and mapping (which do not require sub-meter precision), one parameter that was related to distance calculation from the ‘indicator start’ to ‘turn start’ could have been affected by this GPS uncertainty. Another assumption was that, as the experiment was conducted on open tracks (i.e. not around urban canyons) with clear sky and absolutely no overhead obstructions, given these conditions a GPS provides a horizontal accuracy of +/-5 meters (Londe, 2009). Nevertheless, a GPS receiver with more precision is required for measuring the variables such as distance travelled, position of the indicator switching etc.

Next, the driving behaviours identified were the result of data gathered from the multiple sensors mounted in and outside the test vehicle. Due to the limitations of
the sensors, data related to driver feet movement around the pedals and hand movements around the steering wheel were not monitored. There might be more potential differences when these behaviours are monitored. Moreover, the type of test vehicle used (i.e. a 4WD) is acknowledged as a limitation, since driving this type of vehicle can be daunting for young novice drivers.

Furthermore, it is not known that using this system will actually help the young drivers to improve their behaviour. Although, it is certain that the system has the ability to identify driving manoeuvres performed in a less competent manner and present it to the users of this system.

8.5 Future Work

This thesis is concerned with the development of a model-based framework and its associated tool for the design and evaluation of drivers’ manoeuvring competence, such that the dependability of the assessment can be guaranteed. This thesis opens up a realm of possibilities where future researchers can produce more powerful, user friendly software that can analyse all the possible performance factors with all the variables involved in driving, producing reliable results.

As mentioned previously, that the driving experiment for this research was conducted on a closed loop track using a 4WD. Further experiments on open roads can produce more findings related to the differences in novice and experienced drivers. Nonetheless, there will be issues in terms of ethics, since novice drivers will be asked to perform particular manoeuvres thus effecting road safety. Along with this, different type of vehicles (i.e. sedan, hatchback) can be used to verify the driving performance of both novice and experienced drivers. Furthermore, driving simulators might have issues related to immersion as discussed earlier, but for the safety of participants simulators can also be utilised in designing of complex scenarios that require multiple vehicles on the road or overtake manoeuvres in which vehicles are coming from the opposite direction.

Secondly, more complex manoeuvres can be incorporated into this system to make it more comprehensive. Along with this, additional sensors monitoring more variables related to Driver, Vehicle and Environment will definitely increase the
robustness and effectiveness of this system. Furthermore, a GPS receiver that has a sub-meter precision can improve spatial resolution of the data collected during the experiment. Future work can include the use of a differential GPS receiver for improved accuracy of the results that are computed using GPS data.

Currently the design of the performance assessment models was created after reviewing the results from the driving experiment. This model will only be effective for the parameters defined during the experiment. Future work can include creation of these performance assessment model automatically (utilising Neuro-fuzzy systems) from the driving tasks based solely on the input of driving experience (experienced or novice drivers).

As mentioned above that the on-road research studies reviewed and implemented in this thesis do suggests that training systems have the potential to yield results that can be used by novice drivers to better detect and respond to traffic hazards. However, there has been no regressive evaluation of IDTS results by driver trainers. A more comprehensive study regarding the driver trainer’s view on IDTS in future will help to bridge the gap between the automated training system and driver trainer’s knowledge. These studies will further help to identify the procedure to deal with false positives discovered by IDTS which are not highlighted by the driver trainers, thus improving the overall robustness of the Intelligent Driver Training System. Moreover, regressive evaluation of IDTS will allow the resolution of issues related to false positive results returned from IDTS and user friendliness of the system. Since IDTS performs post-processing of the driving tasks (i.e. it does not display feedback while driving) the issue of non-concurring results (i.e. false positives or false negatives) can be handled by the driver trainer before the feedback is presented to the trainee driver. Eventually the main purpose of the IDTS is to assist driver trainers in their evaluations of the trainee drivers.

A long term study can be conducted based on this system to prove its effectiveness. This will include three groups of drivers. 1) Young drivers that are trained and given feedback using IDTS 2) Young drivers that are trained using conventional training methods 3) Untrained young drivers. After sometime, these groups can be tested
again to confirm if training using Intelligent Driver Training System (IDTS) improved their performance during the driving manoeuvres.


DLink, DGS-2205 5-Port 10/100/1000 Desktop Switch, http://www.dlink.com/products/?pid=494


Gaussian distribution, www.cs.princeton.edu/introcs/11gaussian/


Haversine formula, Calculate distance between two Latitude/longitude points http://www.movable-type.co.uk/scripts/latlong.html


Londe, M. (2009), Baseline Accuracy Assessments of Garmin Recreational GPS Receivers, Geodesist, Information Management and Technology Group


MobileEye AWS-4000 - http://www.mobileye.com/


RTMaps, Intempora, RTMaps software Development Kit Version 3.0, Developer’s manual.


World health organization (2009), Global status report on road safety. Report


Turns & T-Crossings Assessment

Figure A1: Trapezoidal membership functions for the two fuzzy sets used in manoeuvre assessments. The values (a1-e1, a2-e2 and Set1-Set2) are shown in tables for assessments (i.e. Table A1,A2,A3)

a – Lane Keeping Competency Assessments

| Fuzzy ‘Set 1’ | a1 | 60 |
| Distance (centimetres) from right lane | b1 | 80 |
| | c1 | 105 |
| | d1 | 110 |

| Fuzzy ‘Set 2’ | a2 | 20 |
| Average Speed (km/h) during the turn | b2 | 40 |
| | c2 | 60 |
| | d2 | 80 |

Table A1: Fuzzy sets and the membership values used in lane keeping competency evaluation

<table>
<thead>
<tr>
<th>Average Speed during the turn</th>
<th>Distance (centimeter) from right lane</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>Low_Compt.</td>
</tr>
<tr>
<td>High</td>
<td>Low_Compt.</td>
</tr>
</tbody>
</table>

Table R1: The fuzzy rules for evaluating competency of the lane keeping task for turn manoeuvres

*Compt.: competence
b – Following Distance Competency Assessments

### Table A2: Fuzzy sets and the membership values used in lane keeping competency evaluation

<table>
<thead>
<tr>
<th>Average Speed during the turn</th>
<th>Average distance (meters) for the following distance</th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>Low_Compt.</td>
<td>Medium_Compt.</td>
<td>Medium_Compt.</td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>High_Compt.</td>
<td>Low_Compt.</td>
<td>Low_Compt.</td>
<td></td>
</tr>
</tbody>
</table>

### Table R2: The fuzzy rules for evaluating competency of the following distance task for turn manoeuvres

* _Compt.: competence*

**Gaze Depth Competency Assessments**

### Table A3: Fuzzy sets and the membership values used in gaze depth competency evaluation

<table>
<thead>
<tr>
<th>Average Speed during the turn</th>
<th>Average gaze depth (meters) for the turn</th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>High</td>
<td>VeryLow_Compt.</td>
<td>Low_Compt.</td>
<td>High_Compt.</td>
<td></td>
</tr>
</tbody>
</table>

### Table R3: The fuzzy rules for evaluating competency of the gaze depth task for turn manoeuvres

* _Compt.: competence*
Lane Change & Overtake Assessment

Figure B1: Trapezoidal membership functions for the three fuzzy sets used in overtake manoeuvre assessments. The values (a1-e1, a2-e2, a3-h3 and Set1-Set3) are shown in tables for assessments (i.e. Table B1,B2,B3,B4)

a – Following Distance Competency Assessments

<table>
<thead>
<tr>
<th>Following Distance Competency Assessment</th>
<th>a1</th>
<th>b1</th>
<th>c1</th>
<th>d1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fuzzy ‘Set 1’</td>
<td>20</td>
<td>40</td>
<td>60</td>
<td>80</td>
</tr>
<tr>
<td>Average Speed (km/h) during the turn</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fuzzy ‘Set 2’</td>
<td>a2</td>
<td>b2</td>
<td>c2</td>
<td>d2</td>
</tr>
<tr>
<td>Average Following Distance</td>
<td>25</td>
<td>40</td>
<td>45</td>
<td>51</td>
</tr>
</tbody>
</table>

Table B1: Fuzzy sets and the membership values used in following distance competency evaluation
Appendix B.

Average Following Distance (meters) during overtake

<table>
<thead>
<tr>
<th></th>
<th>Average Speed to the lane change start</th>
<th>Average Following Distance (meters) during overtake</th>
</tr>
</thead>
</table>

Table R4: The fuzzy rules for evaluating following distance competency evaluation for overtake manoeuvres

*Compt.: competence

b – Indicator Competency Assessments

<table>
<thead>
<tr>
<th>Indicator Competency Assessment</th>
<th>Fuzzy ‘Set 3’</th>
<th>Distance (meters) from indicator start to lane change start</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>a3</td>
<td>14</td>
</tr>
<tr>
<td></td>
<td>b3</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>e3</td>
<td>25</td>
</tr>
<tr>
<td></td>
<td>d3</td>
<td>40</td>
</tr>
<tr>
<td></td>
<td>f3</td>
<td>55</td>
</tr>
<tr>
<td></td>
<td>g3</td>
<td>60</td>
</tr>
<tr>
<td></td>
<td>h3</td>
<td>75</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Indicator Competency Assessment</th>
<th>Fuzzy ‘Set 2’</th>
<th>Average speed (km/h) to the lane change start</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>a2</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>b2</td>
<td>40</td>
</tr>
<tr>
<td></td>
<td>c2</td>
<td>60</td>
</tr>
<tr>
<td></td>
<td>d2</td>
<td>80</td>
</tr>
</tbody>
</table>

Table B2: Fuzzy sets and the membership values used in indicator competency evaluation

Average Speed to the lane change start

<table>
<thead>
<tr>
<th></th>
<th>Average Speed to the lane change start</th>
<th>Distance (meters) from indicator to start to lane change start</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low</td>
<td>Medium Med High/Med Low Very Low/Very High</td>
</tr>
</tbody>
</table>

Table R5: The fuzzy rules for evaluating indicator competency evaluation for overtake and lane change manoeuvres

*Compt.: competence
c – Time Spent In Right lane During Overtake

<table>
<thead>
<tr>
<th>Time Spent During Overtake Competency Assessment</th>
<th></th>
<th>a1</th>
<th></th>
<th>a2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fuzzy ‘Set 1’</td>
<td>b1</td>
<td>-8</td>
<td></td>
<td>b2</td>
</tr>
<tr>
<td>Average Difference in Speed (km/h) to the vehicle being overtaken</td>
<td>c1</td>
<td>5</td>
<td></td>
<td>c2</td>
</tr>
<tr>
<td></td>
<td>d1</td>
<td>8</td>
<td></td>
<td>d2</td>
</tr>
</tbody>
</table>

| Fuzzy ‘Set 2’                                  | a2    | 2    |
| Time spent (seconds) in the right lane          | b2    | 3    |
|                                                 | c2    | 5    |
|                                                 | d2    | 9    |

Table B3: Fuzzy sets and the membership values used in competency assessment of time spent in the right lane during overtake

<table>
<thead>
<tr>
<th>Average Difference in Speed</th>
<th>Time spent (seconds) in the right lane during overtake</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>Low_Compt., Medium_Compt., High_Compt.</td>
</tr>
<tr>
<td>Medium</td>
<td>Medium_Compt., VeryHigh_Compt., High_Compt.</td>
</tr>
<tr>
<td>High</td>
<td>Low_Compt., Medium_Compt., VeryLow_Compt.</td>
</tr>
</tbody>
</table>

Table R6: The fuzzy rules for evaluating competency for time spent in right lane while overtaking.

*d._Compt.: competence*

d – Gaze Depth Competency Assessment

<table>
<thead>
<tr>
<th>Gaze Depth Competency Assessment</th>
<th></th>
<th>a1</th>
<th></th>
<th>a2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fuzzy ‘Set 1’</td>
<td>b1</td>
<td>12</td>
<td></td>
<td>b2</td>
</tr>
<tr>
<td>Average gaze depth (meters) for overtake</td>
<td>c1</td>
<td>35</td>
<td></td>
<td>c2</td>
</tr>
<tr>
<td></td>
<td>d1</td>
<td>50</td>
<td></td>
<td>d2</td>
</tr>
<tr>
<td>Fuzzy ‘Set 2’</td>
<td>a2</td>
<td>30</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average vehicle speed (km/h) during the overtake</td>
<td>b2</td>
<td>45</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>c2</td>
<td>62</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>d2</td>
<td>70</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table B4: Fuzzy sets and the membership values used in gaze depth competency evaluation

<table>
<thead>
<tr>
<th>Average Speed during the overtake</th>
<th>Average gaze depth (meters) during overtake</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>Medium_Compt., Medium_Compt., VeryHigh_Compt.</td>
</tr>
<tr>
<td>Medium</td>
<td>Low_Compt., Low_Compt., VeryHigh_Compt.</td>
</tr>
<tr>
<td>High</td>
<td>VeryLow_Compt., Low_Compt., High_Compt.</td>
</tr>
</tbody>
</table>

Table R7: The fuzzy rules for evaluating competency of the gaze depth task for overtake manoeuvres

*_Compt.: competence*_
Glossary

Capability: refers to the momentary ability of the driver to deliver his or her level of competence. It refers to what the driver actually is able to do at any given moment.

Competence: refers to the driver’s attainment in the range of skills broadly described as roadcraft, a concept which includes control skills, ability to read the road (hazard detection and recognition), and anticipatory and defensive driving skills.

Driving Behaviour: is related to what a driver does.

Driving Performance: is related to what a driver can do.

Driver training: relates to car control or to the techniques of handling a vehicle.

Driver education: is a broader term which may include driver training but extends to a fuller knowledge and understanding of the driving task in all its complexity.