Intelligent automotive safety systems: the third age challenge

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INTELLIGENT AUTOMOTIVE SAFETY SYSTEMS:

THE THIRD AGE CHALLENGE

By

Imran Amin

A Doctoral Thesis
Submitted in partial fulfilment of the requirement
for the award of Doctor of Philosophy
of Loughborough University

December 2006

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Abstract

Over 300,000 individuals are injured every year by vehicle-related accidents in the United Kingdom alone. Government and the vehicle manufacturers are not only bringing new legislation but are also investing in vehicle safety research to bring this figure down.

A private self-driven car is an important factor in maintaining the independence and quality of life of the third age individuals. However, since older people bring deterioration of cognitive, physical and visual abilities, resulting in slower reaction times and lapses while driving. The third age individuals are involved in more vehicle-related accidents than middle-aged individuals. This scenario is corrected by the fact that the number of third age individuals is increasing, especially in developed countries. It is expected that the percentage of third age individuals in the United Kingdom will increase to 20% of the total population by 2010.

Several safety systems have been developed by the automotive industry including intelligent airbags, Electronic Stability Control (ESC) and pre-tensioned seat belts, but nothing has been specifically developed for the third age-related problems.

This thesis proposes a driver posture identification system using low resolution infrared imaging. The use of a low resolution thermal imager provides a reliable non-contact based posture identification system at a relatively low cost and is shown to provide robust performance over a wide range of conditions. The low resolution also protects the privacy of the driver.

In order to develop the proposed safety system an Artificial Intelligent Thermal Imaging algorithm (AITI) is created in MatLAB. Experimentation is conducted in real and simulated environments, with human subjects, to evaluate the results of the algorithm.

The result shows that the safety system is able to identify eighteen different driving postures. The system also provides other valuable information about the driver such as driver physical built, fatigue, smoking, mobile phone usage, eye-height and trunk stability. It is clear that in incorporating this safety system in the overall automotive central strategy, better safety for third age individuals can be achieved.

This thesis provides various contributions to knowledge including a novel neural network design, a safety system using low resolution infrared imager and an algorithm that can identify driver posture.

Keywords: Vehicle Safety, Infrared, Third Age, Artificial Neural Network, Image Processing.
Acknowledgements

First I would like to say Alhamdulliah, and thanks to Allah for giving me write this thesis.

Many people are due thanks particularly Mr Andrew J Taylor and Professor Rob Parkin for their support as supervisors. I would also like to thank all my colleagues at Mechatronics Research Centre for their help and support.

Special thank to my parents Jawaid Amin and Shahzadi Urfana for their support, encouragement and prayers, without which I could not have finished this thesis.
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Nomenclature

\[ p = \text{Energy Radiated} \]
\[ \lambda = \text{Wavelength} \]
\[ T = \text{Temperature (Kelvin)} \]
\[ h = \text{Plank's Constant} \]
\[ c = \text{Velocity of light} \]
\[ b = \text{Boltzmann Constant} \]
\[ w = \text{Radiated energy} \]
\[ \varepsilon = \text{Emissivity} \]
\[ \eta = \text{Boltzmann constant} \]
\[ T = \text{Temperature (Kelvin)} \]
\[ t_j = \text{Desired or target response for } i\text{th unit} \]
\[ y_j = \text{Actually produced response for } i\text{th unit} \]
\[ E = \text{Error calculated for adjustment of synaptic weights} \]
\[ u_i = \text{Centre of activation functions} \]
\[ q_i = \text{Parameter for optimization} \]
\[ p(v_j) = \text{Polynomial} \]
\[ \sigma = \text{Activation function} \]
\[ j = \text{Number of neurons} \]
\[ q = \text{Point at which interpolation takes place} \]
\[ P(q) = \text{Interpolated value} \]
\[ f_i = \text{Known values on the grid at points } (q_i) \]
\[ L_j(q) = \text{Lagrange polynomial} \]
\[ D_1 = \text{Distance from imager to point of interest} \]
\[ A = \text{Distance between steering wheel axis and thermal imager} \]
\[ D = \text{Distance between driver and steering wheel} \]
**Acronyms**

<table>
<thead>
<tr>
<th>Acronym</th>
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<tbody>
<tr>
<td>ABS</td>
<td>Anti-lock brakes</td>
</tr>
<tr>
<td>ACC</td>
<td>Adaptive cruise control</td>
</tr>
<tr>
<td>AD</td>
<td>Alzheimer disease</td>
</tr>
<tr>
<td>AI</td>
<td>Artificial intelligence</td>
</tr>
<tr>
<td>AITI</td>
<td>Artificial intelligence thermal imaging</td>
</tr>
<tr>
<td>ANN</td>
<td>Artificial neural network</td>
</tr>
<tr>
<td>ASCII</td>
<td>American Standard Code for Information Interchange</td>
</tr>
<tr>
<td>ATM</td>
<td>Automated teller machines</td>
</tr>
<tr>
<td>BAE</td>
<td>British aerospace engineering</td>
</tr>
<tr>
<td>BPN</td>
<td>Back propagation neural network</td>
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<tr>
<td>BS</td>
<td>British standard</td>
</tr>
<tr>
<td>CBA</td>
<td>Cost benefit analysis</td>
</tr>
<tr>
<td>CCD</td>
<td>Charged coupled device</td>
</tr>
<tr>
<td>CI</td>
<td>Computational intelligence</td>
</tr>
<tr>
<td>CMOS</td>
<td>Complementary metal-oxide semiconductor</td>
</tr>
<tr>
<td>CPU</td>
<td>Central processing unit</td>
</tr>
<tr>
<td>DAC</td>
<td>Digital acquisition card</td>
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<tr>
<td>DUID</td>
<td>Driving under the influence of drugs</td>
</tr>
<tr>
<td>EOTR</td>
<td>Eyes of the road</td>
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<td>Electronic stability control</td>
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<td>ESRI</td>
<td>Ergonomics safety research institute</td>
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<tr>
<td>FFB</td>
<td>Feed forward back propagation neural network</td>
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<td>FIR</td>
<td>Far Infrared</td>
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<td>FLRS</td>
<td>Forward looking radar sensor</td>
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<td>FPS</td>
<td>Frames per second</td>
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<td>GHz</td>
<td>Giga hertz</td>
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<tr>
<td>GPS</td>
<td>Global positioning system</td>
</tr>
<tr>
<td>HDD</td>
<td>Hard Disk Drive</td>
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<tr>
<td>HUD</td>
<td>Heads up display</td>
</tr>
<tr>
<td>IIR</td>
<td>Intermediate infrared</td>
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<tr>
<td>ITS</td>
<td>Intelligent transport system</td>
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<tr>
<td>IR</td>
<td>Infrared</td>
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<tr>
<td>LED</td>
<td>Light emitting diode</td>
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<tr>
<td>LCD</td>
<td>Liquid crystal display</td>
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<tr>
<td>LWIR</td>
<td>Long wavelength Infrared</td>
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<tr>
<td>MLP</td>
<td>Multi layered perceptrons</td>
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<tr>
<td>MOMSSE</td>
<td>Mattis organic mental syndrome screening examination</td>
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<td>MWIR</td>
<td>Medium wavelength infrared</td>
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<td>NHTSA</td>
<td>National highway transport safety administration</td>
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<tr>
<td>NIR</td>
<td>Near Infrared</td>
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<td>NODS</td>
<td>Near object detection sensors</td>
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<td>OOP</td>
<td>Out of position</td>
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<td>RAM</td>
<td>Random access memory</td>
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<td>RBF</td>
<td>Radial basis function</td>
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<td>RBN</td>
<td>Radial basis neural network</td>
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<td>RGB</td>
<td>Red green blue</td>
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<td>RPM</td>
<td>Revolutions per minute</td>
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<tr>
<td>SAB</td>
<td>Side airbag</td>
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<tr>
<td>SOM</td>
<td>Self organized map neural network</td>
</tr>
<tr>
<td>SDL</td>
<td>Simple scenario definition language</td>
</tr>
<tr>
<td>SWIR</td>
<td>Short wavelength Infrared</td>
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<tr>
<td>TRL</td>
<td>Transport research laboratories</td>
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<tr>
<td>UFPA</td>
<td>Un-cooled focal plane array</td>
</tr>
<tr>
<td>WDM</td>
<td>Windows Driver Model</td>
</tr>
<tr>
<td>WHO</td>
<td>World health organization</td>
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1. Introduction

In 2002, 3431 people were killed and 35,976 seriously injured by vehicle accidents in Great Britain alone (see Figure 1-1) (DFT, 2002). Even though Great Britain has the lowest traffic related fatalities per capita and per kilometre of travel than any other developed nation, total casualties are still 300,000 per year as shown in Figure 1-1, which includes slight injuries. The U.K. government proposed a target of 40 percent reduction in fatalities and serious injuries by 2010 (DETR, 2000). Improvements in vehicle design, road safety regulations and road system design led to a 13 percent decrease in fatalities from 1999 to 2002 (DFT, 2002).

![Figure 1-1 Road accident casualties in UK from 1992 to 2002 (DFT, 2002)](image)

Much research is being carried out by the automobile industry to make automobiles safer with preference now being given to the use of intelligent sensors. Modern electronics can, for example, help see through night, fog or even forecast an approaching vehicle at a blind turn. Technologies like millimetre wave radars,
Intelligent Automotive Safety Systems: The Third Age Challenge

Infrared sensors, satellite tracking, ultrasonics, laser scanners and magnetic sensors are being rapidly adopted by automobile manufacturers (Dixit, 1998).

Passive safety is nowadays a standard feature in every automobile. When comparing passive safety with active safety systems findings by the Society of Motor Manufacturers and Traders reported that 58 percent of people were unaware of any active safety system (Pullin, 2005). There is no agreed definition of active safety. However, it can be best described as use of technologies that help to avoid accidents and improve the safety situation of the car for the occupant and other road users. Methods discussed in this thesis are mostly related to active safety in cars.

The automotive industry classifies safety into primary and secondary safety. Primary safety is concerned with prevention of an accident before it happens. For example, intelligent sensors like ABS braking systems, lane departure systems and forward looking radar systems are primary safety sensors. Secondary safety is concerned with reduction in the effect and impact of the crash during an accident. The main concern of a secondary safety system is to prevent damage to the vehicle's passenger cabin and reduce risk of injury to the occupants. An example of secondary safety sensors are seat belts, airbags, side airbags.

Drivers under the influence of alcohol, drugs tiredness, fatigue or stress present a high risk of accidents. The automobile industry is pushing towards active safety systems that can warn the driver before an accident happens. Thus technologies like intelligent sensors that can detect out of position drivers, intelligent airbags and driver position monitoring sensors have started to appear.

1.1. Third age drivers

The demographic time change in the last century and reductions in mortality and birth rate (Hitchcock et al., 2001, Dissanayake et al., 2002, WHO, 1998) have resulted in an increase of the ageing population in the developed countries. Europe, the United States, Japan and elsewhere have now proportionally a greater number of
older people than at any other stage in history. In the United Kingdom 18.11 percent of the population is over retirement age and 35 percent of the labour force is over 45. It is estimated that 20 percent of the United States population will be over 65 years and over 70 years in the United Kingdom by 2030 (WHO, 1998). According to the World Health Organization (WHO) the population of the world over the age of 60 will increase from 580 Million in 1998 to 1000 Million in 2020.

The term “Third Age” applies to those aged 55+, although this definition is not universally accepted (Reuben, 1993, D. Carr, 1994). The third age term is not simply used for persons over 55, but the old adage of ‘You’re as old as you feel’ holds true. Those over 55 year old will clearly have a greater impact on designing needs in the future society. But as the grey, or ‘third age’, population increases the products in the consumer market mostly are not adapting to ‘third age’ people’s living style and their habits. As for older drivers, it has been established that driving abilities deteriorate with age, which is a matter of concern for developed nations. The term ‘third age’ is used for people who are not only old but also have some kind of impairment, which may be due to old age or some disability that can occur in old age. Old people, sometimes even in their sixties or seventies, are more active than younger people. These old people are not included in the ‘third age’ definition.

A survey by the National Research Council, U.S.A, (Benekohal et al., 1994) indicated that 70 percent of older drivers used their cars at least 5 days a week, and a higher proportion of male drivers than female drivers drove 7 days a week. As age increases, urban road use increases and highway use decreases. A Transport Research Laboratory (TRL) report (Simms, May 1992) indicated that drivers over 70 commonly use a car for purposes like shopping or going to the bank. Ninety percent (90%) make these trips on weekly basis and eighty percent (80%) make a monthly visit to relatives. One in four fatalities by car accident in the United Kingdom is of third age people. Statistics also show that elderly drivers are the second most likely group to have accidents after 17 to 24 year old drivers.

Many researchers suggest that the age factor does cause a decoration in driving skills. Third age drivers become vulnerable with age (Reuben, 1993). For Older
drivers it is difficult to navigate while driving (May et al., 2005). Deterioration of vision, tunnel vision, and restriction of movement in limbs are some of the symptoms that affect them.

1.2. Motivation for research

The topic for this research is ‘intelligent automotive safety systems: the third age challenge’. ‘Third age’ people have age-related impairments which may affect their driving skills. These driver problems include symptoms such as restriction of movements in limbs and slower reaction time. Vision becomes worse significantly which requires other body parts to compensate for the deterioration in vision. For example tunnel vision requires more head movement. Driving is challenging for third age people and this results in increased errors, lapses and violations while driving. Due to these impairments some particular accident circumstances can cause fatality or severe injuries to elderly drivers.

This project is primarily concerned with the investigation of an intelligent safety system. Driver problems are discussed in detail in later chapters. The motivation for this research came from the global focus towards inclusive design. As the grey population increases in developed countries more focus is towards the third age population. Growing markets and stricter government regulations are major incentives for designers to design products for third age people.

The ‘inclusive design’ term is about ensuring that surroundings, products and services are usable by all ages and abilities. For inclusive design, designers make sure that the product and service is available to the widest possible audiences. This includes third age people and disabled people which were previously ignored by mainstream design practices. New global legislation (BS-7000-6, 2004) was introduced in 2004. This legislation forces designers, manufacturers and service providers not to discriminate against people on the basis of age or capabilities.
Intelligent Automotive Safety Systems: The Third Age Challenge

Infrared imagers were used previously for research and development in fields like high technology defence and aerospace applications. As the price of thermal imagers goes down, other industries are also starting to research into thermal imaging technology. Low resolution thermal imaging has recently been introduced for commercial and industrial applications by infrared imager manufacturers. Low resolution thermal imaging technology is still in its infancy but holds significant potential. Some of the applications for low resolution thermal imaging include condition monitoring, automated people-counting, obstruction detection, intelligent surveillance and intelligent vehicle vision.

1.3. Aim of research

The main aim of this research is to investigate means of identifying driver postures, movements and behaviours which indicate a high level of risk, particularly for older or impaired drivers. The identification method will use a low resolution IRISYS infrared imager making the identification method non-contact, potentially cost effective and ideally feasible for use in cars produced within the next five years. Eventually the safety system will provide information to the centrally controlled safety system.

For the third age and disabled drivers the safety system will be useful if it can identify restriction of movement in their limbs or neck, or slower reaction times. The safety system will also be useful for identifying young driver problems that might include, for example, ignoring crucial driving tasks like looking both ways at an intersection and dynamic allocation of attention. Additionally the safety system can be used as a tool that can give information about the driver and their driving patterns to a researcher. This information will help to identify driver problems, especially for third age drivers and impaired drivers, when used offline in conjunction with other sensors. The identification of driving behaviour could also lead to offline comparison of different driving patterns of young and third age drivers.
This research will only be concerned with identification of driver postures. Infrared imaging has been chosen because it is a non-contact method. It is also insensitive to ambient noise and lighting variations. It seeks body heat which, in the wide range of conditions encountered in cars, makes infrared imaging a more reliable approach than other systems such as ultrasonic, visual cameras, radar and laser based sensors. The infrared imager used for this research is a low cost device with low resolution which provides much needed privacy to drivers in cars. This is not possible using conventional visual cameras which may be perceived as being intrusive (see Section 5.1.1). A major part of the research will be the development of a safety system based on a non-contact method using a low-resolution infrared imager, the IRISYS thermal imager.

1.4. Scope

Currently there is no such low resolution, low cost thermal imaging based safety system in automobiles that can give information about the driver and passengers. A few visual based systems are available and are still under research. These visual systems are mostly being used for intelligent airbag deployment.

By using Thermal Imaging the safety system can identify the driver's movement. Finding restriction of movements (upper half) for 'third age' and 'impaired' drivers will give us insight into their driving habits. This can be seen as a new safety sensor for intelligent automobiles, which can find flaws in the driving habits and warn before an accident happens. It can be classified mainly as a primary safety system. However, in addition to this the detection of out of position (OOP) occupants will make this system also classify as a secondary safety system.
1.5. **Boundaries of the research**

The thesis is focused on investigation of the safety system which detects driver postures and movements. It explores the technical side of the sensor system and the driving postures.

1. The focus is on the development of a safety system not the development of the sensor. The safety system will only provide posture related information to the central safety unit for appropriate action.

2. The safety system will be an offline reporting system.

3. The safety system will be based on driver posture.

1.6. **Methodology**

The research consists of several stages comprising literature review, technology and safety system proposal. These stages are then classified into sub stages as shown in Figure 1-2. The proposed safety system stage is the major part of the research. The sub-stage: experimentation will involve testing and proving the algorithm developed in the earlier stage.
A thermal image processing algorithm is developed in stage 2 after finalising the position of the IR imager. A novel neural network is designed. Test runs are done in a driving simulator and IR thermographs are acquired using the IRISYS imager. To these IR thermographs the imaging algorithm is applied and then simulated using the neural network.

After the ‘development of safety system’ sub-stage, a broad range of human subjects is selected based on their age and gender. More experimental runs in the driving simulator are done. The results are then compared offline and driving patterns are discussed. The low resolution IRISYS thermal imager is used as the main tool in the experiments. Infrared acquisition and visual acquisition software, developed by the author, is used in the experiment sub-stage to acquire thermographs from the IRISYS imager (Amin, 2003).

1.7. Thesis outline

The thesis is organized as follows:
Intelligent Automotive Safety Systems: The Third Age Challenge

Chapter 1: Introduction
This chapter gives a brief background to the field and explores the motivation behind the research. It establishes the aims and scope of the research. The methodology of research is also explained briefly in this chapter.

Chapter 2: Literature Review
This chapter discusses what previous research has been done in the field related to this research.

Chapter 3: Technical Background
This chapter gives detail about the technologies, sensors and tools that will be used and related to the research carried out in this thesis

Chapter 4: Hypothesis
This brief chapter gives the research questions which will be addressed in this thesis.

Chapter 5: Imaging Techniques and Image Processing Algorithms
This chapter is concerned with the actual imaging algorithm development and the techniques that are used during this process.

Chapter 6: Artificial Neural Network
This chapter goes through the design, training and implementing of the neural networks. Optimization of the neural network is discussed based on the design and modified accordingly.

Chapter 7: Experimental Setup
The experimental runs are done to evaluate the imaging algorithm. This chapter explains in detail the kind of experiments that are conducted.
Chapter 8: Results and Discussion

This chapter gives the results obtained from the neural networks and its discussion. The chapter also discusses the system capabilities. It will address the research questions stated in chapter 4 in a systematic manner.

Chapter 9: Conclusions and Further Work

This is the concluding chapter of this thesis and also suggests directions for further work.

1.8. **Summary**

- Vehicle safety is a major issue of concern even for developed countries. Governments and automobile manufacturers are taking steps to make roads safer for drivers and pedestrians. Extensive research is being done in this field to develop intelligent sensors that will aid the drivers or make their driving safer.

- There are a group of drivers that are identified as a safety concern on the road, especially for developed countries. This group is termed the "Third Age" drivers. This term applied mostly to old drivers who are over the age of 55 with some exceptions. Their driving abilities deteriorate with age. This age group will represent around 20% of the population in the near future.

- This research proposes a non-contact non-intrusive alternative for identifying driver movements. This system should be an inclusively designed safety system.

- There is an extensive use of thermal imaging in defence and other industrial applications. Currently no low resolution intelligent thermal imaging solutions exist for vehicle safety systems.
• The research will be based on technology, proposed safety system design, experimentation and evaluation of the safety system.
2. Literature Review

This chapter uses previous literature and research for common driving problems faced by the drivers. It also discusses previously researched sensors and safety systems. Most of the problems discussed are due to the physical limitations of the drivers. Further on this chapter focuses in detail on the Third age driving problems. Recent developments in vehicle safety systems are then discussed.

2.1. General driver problems

There are many driving problems that are frequently encountered by drivers. Not all of them can be discussed in this literature review as the list will grow significantly. Only major driver problems and issues are discussed and related research is reviewed. These driver problems are interrelated and some topics do overlap but are discussed from a different perspective as required.

2.1.1. Young age drivers

According to a research survey (Williams et al., 1997), young beginner drivers are three times more at risk than middle-aged drivers. In 40% of the fatal accidents occurring at night time, 16 to 17 year old drivers are involved. Young drivers are at elevated risk of an accident when accompanied by multiple passengers. The risk increases four to five times compared with driving alone.

Recent research (Lucidi et al., 2006, Monarrez-Espino et al., 2006) provides statistics of accidents by age groups and their causes. This shows that drivers under
the age of 30 years are at high risk of accidents during the early morning, whereas drivers from 17 to 24 are 10 times at higher risk at late night driving than at noon. This higher risk of accidents in this age range is due to less experience and knowledge of how to cope with fatigue. Young drivers usually overestimate their driving abilities. The research was questionnaire based in which participants from 18 to 22 years old with driving experience of not more than 2 years were selected. About 15% of participants said that they had not driven a car between midnight and 0500 hrs in the last 6 months. Of the ones driving between these hours 46.6% experience impairment by sleepiness at least once a month. 41.3% of young male drivers experienced severe sleepiness compared to 27.1% of female drivers.

2.1.2. Driver distraction

Driving alone, when not involved in distracting activities, time sharing tasks are performed concurrently by the driver. These crucial tasks involve staying on the road, changing lanes, checking mirrors, reacting to changes and maintaining forward motion. Other secondary tasks are slightly less important like checking speed or road signs. When the driver is distracted both crucial and secondary tasks suffer.

Mobile phone users are four times more likely to have an accident than an average driver. Researchers found larger steering movements while doing crucial tasks, delayed braking patterns and slow reaction to critical signals (DFT, 2002).

An experiment was conducted with the help of 36 young drivers using a mobile phone while driving on a STISIM driving simulator (Beede et al., 2006). During this experiment drivers received phone calls using a headphone and speaking pieces. Participants driving performance is divided into four categories: violations, attention lapses, driving maintenance and reaction time. Results showed that 67% of the participants had at least one accident. 61% of the participants were speeding while using a mobile phone. Participating drivers took one-third of a second longer to set off after the car came to a stop sign when engaged in telephone conversation. In a
Intelligent Automotive Safety Systems: The Third Age Challenge

separate driving questionnaire 80% of drivers said they engaged in hand held mobile phone conversation at least once a week with an average of 8.4 minute conversation everyday. Participants reported an average driving distance of 15 miles per day. Participants managed to narrow their attention to more crucial driving tasks with not much concentration given to secondary driving tasks.

2.1.3. Drink and Drugs risk

A research paper (Pack et al., 1995) regarding illegal drugs intake and its effects whilst driving confirms that illegal drugs like cannabinoids, cocaine, lysergic acid diethylamide, amphetamine and ecstasy cause symptoms that can cause fatal accidents. Young teenage drivers are more involved in drugs and drink driving. Drinking and taking illegal drugs can leave the user with distorted perception, confusion, blurred vision, anxiety, nausea and over confidence. Also after several hours the users will experience severe fatigue and tiredness.

Research (Augsburger et al., 2005) conducted in Switzerland shows that illegal drugs are also known to cause impaired driving skills by affecting attention abilities, visual acuity, judgement, reaction time, drowsiness etc. Thus multiple medication intakes also increase the risk of road accidents. Police took blood and urine samples from the patients who fitted the criteria of being alive at least 24 hours after the accident and having the documentary proof of DUID (driving under the influence of drugs). The experiment was conducted with 440 subjects who met the selection criteria. The results showed that 91% of drivers who crashed under the influence of drugs are males. Mean age of the drivers was 28. The most common drug used was cannabinoids at 59% and ethanol (alcohol intoxicant) was at 49%. Other drugs were opiates (9%) and cocaine (13%). The authors concluded that suspicion of impaired drivers is highly correlated to drug analysis in blood and that young male drivers are at higher risk than female and older drivers.
2.1.4. Sleepiness and fatigue

An asleep driver is defined as the driver who fell asleep while driving prior to a crash (Stutts et al., 2003). A fatigued driver does not necessarily have to be asleep and is classed as drowsy, or physically tired. Fatigue is defined as temporary loss of strength due to mental or physical work or tiredness caused by stress. Fatigue will lead to sleepiness which is a very sleepy state. A mail-based survey was conducted by the same author in the US, with more than 1400 drivers from North Carolina involved in the study. In the survey more than 23% of drivers that had accidents in the past related to fatigue said that drowsiness was not important at all. Drivers involved in sleep related crashes are more likely to have problems sleeping or have trouble falling sleep. Long driving trips is also another factor which increases the likelihood of having a sleep related crash. Nearly 8% of the sleep crashes involved alcohol intoxicated drowsiness.

It is a well known fact that sleepiness causes driving accidents (Gold et al., 1992, Stutts et al., 2003, Pack et al., 1995, Bunn et al., 2005). The symptoms of sleepiness include eye problems, yawning, difficulties staying alert, and task focus (van den Berg et al., 2006). The crashes occurring due to drowsiness mostly involve young persons, night shift or rotating shift workers, persons with undiagnosed or untreated sleep disorders and drivers under the influence of soporific medications or sedating medicines. Medical conditions are another factor that causes sleepiness or drowsiness while driving. Drivers suffering from sleep apnoea are prone to fall asleep up to 700% percent more than regular drivers. This becomes very dangerous when driving on a motorway. In the U.S 5.1% of accidents are related to fatigue, drowsiness and lack of concentration, especially in large vehicles. This is because truck drivers are always considered at more risk due to their long driving hours. When drivers lack sleep they are easily distracted and are less alert.

Research published by the BBC (BBC, 2005) describes how they were able to spot sleepy drivers early without going on the road. The results suggest that drivers that usually drowse while driving will do the same when driving in a driving simulator.
As patients with sleep apnoea have very high risk of having an accident, the research team suggested that driving simulators can be used as a benchmark parameter of driving performance for sleep apnoea patients. One of the symptoms of sleep apnoea syndrome is a disorder that causes daytime sleep.

From the above it can be established that sleep or drowsiness can be a critical issue while driving. This has caused many accidents alone. Taking it further it can be found that sleep disorders are common in middle aged males. In a survey conducted by (Krahn et al., 2006) it was found that 49% of middle aged men with heart conditions suffer from sleep apnoea. Also relating to heart diseases, Javaheri (Javaheri, 2006) conducted research on sleep related breathing disorders. Sleep related breathing disorders are known to occur in a patient with heart failure. Significantly obese drivers also have breathing disorders and develop snoring in many cases. Snoring can be related to heart condition and sleeping disorders.

### 2.1.5. Disabled drivers

In some countries it is required by law that a disabled person should be engaged in activities in the same level as that of other people (Falkmer et al., 2000). Driving is one of the most important factors that can increase quality of life by spontaneous mobility.

TRL conducted a study on disabled drivers' controls and car conversions (Ergonomics, 1986). Even though the study is quite outdated, it still forms the basis of car controls used nowadays. The findings from the research report are discussed. Several types of controls are developed for disabled driver including drive by wire systems, foot steering wheel systems, horizontal steering systems, knee operated steering, ultra light steering wheels and shoulder operated brakes. Voice and infrared sensors are being used for non critical functions like activating GPS and radio. In the UK rod mounted brakes are most common. Foot steering systems are getting more and more common and commercially available. Most difficulty in driving comes
Intelligent Automotive Safety Systems: The Third Age Challenge

from people who are suffering from neurological problem and severe weakness. Making controls for this group of disabled drivers is more expensive. There is no regulation or standard for mounting and installing of car controls, it varies from individual to individual. Car simulators are also being used to find out drivers' ability to drive using these special controls.

Stability and psychomotor skills are of utmost importance for disabled drivers (Geiger et al., 2004). Stress tolerance and reaction time is also one of the major factors that affects third age drivers and most prominently disabled drivers. Driving on the road for disabled and elderly people can be a challenging task, physically and mentally.

2.1.6. Driver's Vision

Driving is to a very high extent a vision task. Vision impairment, vision obstruction, and blind spots, identifying obstructions while reversing should be investigated. Vision occlusion while driving is considered to be a major factor in accidents and collisions; instrumentations and techniques are created to mimic vision occlusion and experiments are conducted by ergonomic practitioners to measure the effect of vision occlusion while driving (Noy et al., 2004, van der Horst, 2004, Baumann et al., 2004).

2.1.7. Third age drivers and age related disabilities

An eighty year old woman is four times more likely to die in car crash than a twenty year old man. Third age drivers have the highest fatality rate of any driver age group. The third age driver will have more lapses (though not violations) than any other driver. These lapses will result in not carrying out tasks which are essential in driving including looking left and right. It is seen from annual statistics that most third age
Intelligent Automotive Safety Systems: The Third Age Challenge

that most third age driver accidents occur at junctions. This is due to lack of neck movement (Hu et al., 1998).

A driver can take his eyes off the road for a maximum of 1.5 seconds. More than 1.5 seconds is dangerous, especially when driving on a motorway (Parker et al., 2000). As the reaction time gets slower for older people the time needed to look away increases. Third age drivers are known to have taken double the time it takes middle aged drivers to complete a certain task while driving.

A survey was conducted in Manchester, U.K. in 1989 of drivers aged 50 or over (Parker et al., 2000). The survey mentioned three types of driving problem:

1. Errors

2. Lapses

3. Violations

Errors are driving mistakes and can have serious consequences. Lapses are primarily unintentional failures, which cause embarrassment, but there is no direct impact on safety. Violations are risky driving behaviours, which the driver engages in deliberately. Some of the most frequent driving errors, lapses and violations by the 50+ aging community are as follows:

Errors while driving:

- Unable to estimate the speed while overtaking a vehicle.

- Braking quickly on a wet/slippery road.

- While changing lanes, forget to check rear view mirror
Lapses while driving:

- Misreading signs and taking a wrong turn from roundabout.
- Wrong lanes taken while approaching a roundabout.
- Forgetting where the car is parked.
- While driving towards destination A, you notice that you are off to destination B, which is a more usual route.

Violations while driving

- Disregarding speed limits during non-rush hours.
- Becoming impatient with a slow driver, in front and undertaking the vehicle.

A passive accident is one in which the driver’s vehicle is hit by another vehicle and vice versa in the case of an active accident. If the active-passive ratio is greater than one (1) it means that the driver is involved in more active accidents than passive ones and if the active-passive ratio is below one (1) the driver of that vehicle is less likely to be at fault as he has been involved in more passive accidents than active accidents (Parker et al., 2000).

Looking at age trends over the whole sample in factor scores, they showed that violations decrease with age. At the age of 50 violations levelled off with the lapses. As the age increases from 50 to onwards the number of accidents decreases as they go out less frequently but the number of ‘active/passive accidents ratio’ increases considerably from 0.95 for 59 years and less to 1.44 for 75 years and older (Parker et al., 2000).
The potential factors that contribute towards having a vehicle crash by older people are (Hu et al., 1998):

- Demographic attributes
- Limitations or restriction in carrying out physical activities
- Chronic conditions
- Physical features
- Psychosocial features
- Symptoms
- Drug usage
- Health related factors

**Vision problems in third age drivers**

The size of the useful visual field of work is not always the same. It changes with situation, time and tasks being conducted (Sanders, 1970). The ability to detect peripheral signals in more than one task worsens with age. Thus older driver's performance is much poorer than their younger counterparts.

Research shows that the 40% reduction in visual field by third age people significantly increases the risk of accidents while driving. Further research reveals that vision field deterioration is directly related to tunnel vision phenomenon (Roge et al., 2003, Seiple et al., 1996).
A study was done by Roge *et al.* (Roge *et al.*, 2002) on visual impairment and states of vigilance while driving. Car driving is a complex task which involves vision modality to a high degree. A degree of visual impairment does not necessarily mean bad driving as the subject will compensate for an artificially generated deficiency. In the experiments conducted the artificial visual impairment was created by wearing goggles. The field of view was worsened while performing a similar task like driving for a prolonged period. The vision signals appear to be in 5 to 20 degrees, and tunnel vision phenomenon also occurs. In the experiments conducted by Roge the field of view for the driving simulator was restricted to 50 degrees horizontally and 25 degrees vertically. Also the driving was carried out in a fog scene. In which the subjects had to follow a car with an average speed of 110km/hr. During the experiment the subjects were presented with a peripheral signal, a momentary visual point in the simulation, at different eccentricities (5°, 10°, 15° and 20°). It's was also found during the study that as the tunnel vision angle decreases the occupant becomes drowsy and two subjects fell asleep. Eighty peripheral signals were presented at different eccentricities every half hour and the subject had to respond by flashing the head lights to full beam as quickly as possible. Each experimental run consisted of a 2 hour run without any interruption to the driver. It was noticed that as the eccentricity of peripheral signals increased the performance deteriorated. For example male subjects have an accuracy percentage of 78.4% at 5 degrees of eccentricity which deteriorated to the accuracy percentage of 10.1% at 20 degrees of eccentricity. The central task of following the car at an average speed is also monitored by a central signal. The performance for this central signal deteriorated as that of peripheral signals. For example only a 10% decrease was shown from the first half hour run to the fourth half hour run. It was noticed that fewer corrections to the steering wheel and fewer micro movements are detected with time. Tunnel vision implies that the probability of perceiving signals by a drowsy driver is not constant across the whole visual field.

Visual, physical and cognitive functions decline with age. This in result affects daily tasks, including the ability to drive an automobile safely. A study conducted by McGwin Jr *et al.* (McGwin Jr *et al.*, 2000) involves visual risk factors in older drivers. In the study two groups of older subjects were assembled, the first group including
older drivers with cataracts and the other group without cataracts. Cataract is a medical condition which leads to visual impairment in the older third age drivers. This visual impairment includes visual acuity, contrast sensitivity and visual field sensitivity, thus causing increase difficulty with visual activities of daily living. This medical condition is curable by surgical means. All subjects selected in this study were from 55 year old to 85 year old independently living licensed drivers. The first stage of the study involved collection of demographic information (like age and gender), driving habits, visual function and cognitive status. Eight driving scenarios for example driving in rain, rush hour driving, driving alone and making left turns were selected. The subjects were asked to rate the difficulty from one (1) to five (5), with five (5) being not difficult and one (1) being extremely difficult. In the second stage visual functional status of all participants was measured with respect to visual acuity, contrast sensitivity, disability glare and functional field of view. The visual measurements were taken from speciality charts like logMAR for distance acuity and the Pelli-Robson contrast sensitivity chart. Useful field of view is measured by Visual Attention Analyzer, Model 2000 (Visual Resources, Inc., Chicago, IL, USA). Later cognitive functions were tested in a twenty (20) minutes test. This was done by the Mattis Organic Mental Syndrome Screening Examination (MOMSSE), which is designed to assess cognitive function in the elderly. The author validates his hypothesis that the older drivers with visual impairments have difficulty in specific driving situations. The author concluded that visual acuity and contrast sensitivity are the main concern of safety for older drivers with visual impairments.

**Driving habits of third age people**

Travel by third age people is limited compared with younger people (Cutler *et al.*, 1992, Siren *et al.*, 2004). Very few studies are available for elderly driving behaviour, travelling habits and the factors affecting them. A US study shows that personal transport is not commonly used by the third age people, particularly female gender and urban residents. Most elderly people prefer using public transport as their eyesight and mobility deteriorates and they are unlikely to go out at night in their
cars unless necessary. According to the above study based on the census data of the US, 1.3% rural farm men who are 65 to 74 do not have access to vehicle, while 57.8% of urban living females over the age of 85 do not have access to personal transport and like travelling using public transport. There is less desire for frequent travel and longer distances, and therefore generally less need for mobility.

**Attentional ability**

To keep the car on the road is crucial for safe driving. An experiment with young and elderly drivers was conducted by de Waard et al. (de Waard et al., 2004). Visual information on the driving simulator road was created as follows:

- No delineation
- Centre-line; 3 metre long only
- Centre-line and roadside markers
- Full delineation; includes centre-line, continuous road edge and road side markers
- Full delineation with lampposts

A ghost road was forked from the scenario with only lampposts but no delineation. 81% of younger drivers followed the centreline from where the ghost road is forked, while only 50% of the elderly within the ages of 55 to 70 took the centre line. The rest of them followed the ghost road with only lampposts. Thus older drivers tend to give much more concentration to road elements to predict the position on the road as they are easier to see than the centreline. Elderly drivers also have difficulty in judging and deciding the flow of traffic or in tasks that demand attentional skills (de
Waard et al., 2004, McGwin Jr. et al., 1998). Elderly drivers were more confused than other drivers, and wrong turn probability was over 50%.

In a study conducted by Louis et al. (Louis et al., 2000) two age groups of sixteen subject drivers were selected for the experiment. The first group was of younger drivers under the age of 35 and the second group was of older drivers over the age of 55 years. Each group contained an equal number of male and female drivers. A specially designed test track was used for the experiment which was 7.5 miles long. The test car was equipped with speed measuring, lane departure detection, road-scene camera and driver eye glance behaviour at 30 Hertz sampling rate. The average trial time to complete the experiment run for older driver was twice that of younger drivers. The tasks included using four different types of guidance systems, tuning the radio and dialling a 10 digit manual mobile number. Total seconds of eyes off the road (EOTR) for older driver is twice that of younger drivers. Young drivers took an average of 40 seconds EOTR during the whole test, older drivers took 83 seconds, for tasks including looking down at the radio, mobile phone and guidance system. Advanced navigation and information systems can be dangerous for older drivers. Henderson et al. (Henderson et al., 1999) regard advanced information systems as a two edged sword for third age drivers. This is because of diminishing perceptual and cognitive abilities. Usually a normal driver makes small head movements toward the right and left to get a view of 30 to 35 degrees, secondly the driver adjusts his or her eye for close vision and reacts to the situation accordingly while driving. Older drivers take longer to process the information. The reaction time for older drivers is also slower than younger drivers. Larger head movements to left and right are required to compensate for visual impairment phenomena like tunnel vision.

Driver attention sharing between road and in-vehicle displays was compared between young and older drivers by Mourant et al. (Mourant et al., 2000). The experiment was conducted on a driving simulator. The first age group of ten driving volunteers ranged from the age of 23 to 46, the second age group was from 58 to 76 also ten driving volunteers. A total of 26 trials were done for each volunteer, the first trial being a practice run to familiarize the volunteer with the scene. The response data was collected by superimposing a random four digit number onto a road scene and
verbal response from the volunteer is recorded. The superimposing was done on an in-vehicle display and driving simulator screen, thus causing driver distraction. When the time between stimuli was 1.6 seconds younger drivers had an accuracy of 99% and older drivers had an accuracy of 89%. As the time is decreased to 1 second between stimuli the younger drivers had an accuracy of 73% and the older drivers accuracy reduced to 59%. During the trial runs the older drivers spend 20% more time outside their driving lane than younger drivers, in a driving simulator. The authors suggest that for older drivers, the most difficult number to read is superimposed from the far view rather than the closer in vehicle display. The older drivers also have difficulty in switching between near and far vision.

2.1.8. Safety for third age people: Memory & Motor skills

The skills of third age people deteriorate with age in tasks ranging from driving (Barrett et al., 2000, Holland et al., 1994) to using Automated teller machines (ATM) (Adams et al., 1991, A. Rogers et al., 1997, Rogers et al., 1996) which are considered easier to use by the younger generation and require no training. This will make the third age generation reluctant to adapt to new products due to products involving unfamiliar concepts or procedures, for example use of computerised and interactive technology (Marquie et al., 1994, Rogers et al., 1996, Park et al., 1999).

A study was conducted by Lundberg et al. (Lundberg et al., 1998) on cognitive functions of older drivers, as spatial orientation and speed perception are known to decline with normal ageing. Age related cognitive diseases also create high risk of automobile crashes, particularly diseases like Alzheimer’s Disease (AD). The authors mentions about impaired and third age driver problems which include driving too slow, getting lost and taking wrong turns on roundabouts. The main cause for these problems is cognitive impairments. Third age people with diagnosed cognitive impairments are at high risk while driving. Sixty nine driver-volunteers, over the age of 65 took part in experiments. The experiments were conducted to find the extent of older driver crash involvement due to cognitive impairments. Thirty six drivers had
suspended licenses with twenty-six involved in car crashes. These drivers were compared to thirty one drivers with clean licenses. In addition to neurophysiological examination, a thorough medical examination was conducted which included visuospatial ability, memory, reaction time, psychomotor speed and diverted attention. In the suspended license group four distinguished categories were found:

1. Twenty-four (24) drivers violated intersection rules like not stopping at red traffic lights, not giving right of way, not stopping at Stop signs.

2. Four (4) drivers complained of loss of vehicle control.

3. Two (2) drivers; the cause for license suspension was speeding.

4. There were also priority violations leading to head-on collision, rear end collision, running down pedestrians and, crashing into a railway barrier.

It has been noted that car accidents involving the elderly includes cognitive decrements in memory and visual perceptual skills (Lundberg et al., 1998, McGwin Jr. et al., 1998).

Also there are decrements in speech processing skills like loss of hearing, speech recognition, cognitive inhibition and working memory (Tun et al., 1997, Sharit et al.).

Ergonomics practitioners and design engineers have created tools over the years to over come this deterioration of skills in third age. The hearing aid is one of the most commonly used aids by the end user to over come speech processing problems (Smeeth et al., 2002).
A third age suit in Figure 2-1 created by Hitchcock et al. (Hitchcock et al., 2001, BBC, 2004) gave ergonomics practitioners a new tool which helped them to identify what aspects maybe used in designing a product for third age people. Previously information systems like USERfit were also available (D. Poulson, 1998, D. Poulson, 1996), but none provided design engineers with the information required to design the consumer product. The third age suit allowed the designer to try it on before designing the product. It allowed the designer to feel like a 'third age' person. The third age suit was developed by means of a thorough review of the physiological aspects of the ageing process. Movement restrictors are applied to the wrist, elbow, back of the upper and lower torso, knees and ankles. The suit allowed design engineers to simulate the experiences of third age people while designing or optimizing the application.
2.2. Safety in cars with intelligent sensors

This section explores the recent advances in the field of car safety sensors. The key focus of the literature review in this section is on active and occupant safety components in automobiles. The literature discussed in this section is sub divided into primary and secondary safety.

2.2.1. Primary safety sensors

Pre tension seat belts

The car manufacturer Volvo made the first seat belt in 1949. Even common seatbelts nowadays lock up when a sudden force is applied. The pre-tension seat belt activates a tensioner which pulls tension onto the seat belt prior to maximum impact force occurring.

The most popular type of pre-tension mechanism for a seat belt is pyrotechnics based. On collision the ignition creates a pressure that moves the belt webbing back inside housing. This is achieved usually by a gear rack arrangement as shown in Figure 2-2 but varies from designer to designer.
Rack and pinion arrangement for retracting seat belt

At the time of an accident the ignition fires pushing the rack up to rotate the pinion which retracts the seat belt. (howstuffworks.com)

Figure 2-2: Seat belt pre-tension mechanism

**Radar and ultrasonic sensors**

Over the last decade ‘Short Range Radars’ are increasingly being used in the automotive industry to create a safe ‘intelligent highway control’. ‘Short Range Radars’ are mounted on the front and back of cars to detect any obstruction while driving. These radars are also known as ‘Millimetre radar sensors’ or ‘Short distance radars’ shown in Figure 2-3.

The range of short distance radar sensors is around 20 metres. These radars have frequency 24GHz with relatively short wavelengths of around 4mm. ‘Short Range Radars’ can achieve an accuracy of 10cm to 25cm in determining the position of an object. Short distance radars are used in parking assistance, pre-crash detection, stop and go driving, back-up warning, blind spot detection, side impacts and so on. These radars can work easily in deteriorating weather conditions, like rain, fog, snow and night (Nebot et al., 1999).
Researchers came up with ideas such as autonomous or aided lane changing, side-impact warning, reverse warning, visual aid and collision avoidance by using radar technology (Mar et al., 2003). This radar technology has been developed in automobiles for not only looking behind a vehicle but also it is being used for 360 degrees envelope coverage of the automobile. Near object detection sensors (NODS) are also used for short detection of vehicles and people in the vicinity of the vehicle.

Long-range sensors, or Forward Looking Radar Sensors (FLRS), are used for adaptive cruise control. The Forward Looking Radar Sensor (FLRS) is the most sophisticated sensor system that can detect more than 150 metres at 77 GHz and allows adaptive cruise control according to traffic flow, warning systems like pre-crash detection and some of the vehicle controls, as well by use of signal processing (Macom, 2006).

Rudin-Brown et al. (Rudin-Brown et al., 2004) demonstrated an application of FLRS. It is an extension of conventional cruise control. Allowing a vehicle to follow another vehicle at speed and maintain a constant distance by controlling engine and brake. A vehicle with ACC (adaptive cruise control system) (see Figure 2-4) will increase or decrease speed according to the vehicle in front, and measures a distance with special FLRS radars.
Ultra sonic sensors, depicted in Figure 2-3, are also used in the automotive industry for obstacle detection. Mostly these sensors are used for reverse parking warning systems. Based on a 40 kHz sound pressure wave, the sensor covers a range of 1 to 3 metres detecting objects. As the measuring angle is far greater than the radar systems there is too much noise in these sensors from the backgrounds like road and more angular objects to allow their use for driving situations other than parking.

All these sensors measure distance, but radars can only be used within a limited angle. They also cannot be used to distinguish between different objects. Here intelligent video algorithms and machine system may be used. Stereovision is also used to measure distance between different objects. These videos can tell flow of movement, distance and relative velocity with computer vision.

Visual cameras are used to find the distance of a driver’s head from the steering wheel using stereo vision for intelligent airbag systems. Reading eye pupil gaze movements using visual cameras with a Near Infrared filter is a common technique in which the driver’s gaze is tracked to find fatigue and other vision related driver problems (Boyraz, P., 2006).
Other intelligent car sensors that involve machine vision include lane changing sensors used in intelligent cruise control. Autonomous vehicle steering and vision guidance systems is an active research field. Collision warning systems and obstacle detection is also done using machine vision techniques (Mar et al., 2003 and Bertozzi et al., 2000). The current research emphasis is on stereo based vision systems to bring an extra dimension (depth) into the previously developed vision systems.

Vehicle tracking, detection and classification is now commonly done using machine vision systems installed on busy highways.

**Laser scanners**

Laser sensors can measure distance and angle of the object relative to the car. However they have to be installed on the outside of the vehicle, which is a disadvantage. The range of these types of sensors is around 50 metres.

Laser machine vision is a vast field, in automotive applications the laser sensor is used particularly for distance measurements, a technique called laser range measurement or laser range scanning. This is also a substitute for radar sensors but has been outdated by the use of short wave radar sensors due to the need for expensive laser signal measurement equipment.

Many automotive steering control systems are based on GPS sensors but an alternative method for autonomous guidance, when the satellite navigation signals are blocked, is that of machine vision and laser based radar systems.

Applications that involve laser radar systems include autonomous vehicle navigation, lateral guidance systems, obstacle detection, autonomous service vehicles, walking robot foot placement, manufacturing and quality inspection, military and agriculture.
Night vision (Infrared or Near Infrared vision)

Only one quarter of total driving is done during night time, but half of the traffic fatalities occur at night. Lack of visual information is the main contributor to these accidents. In the last five years night vision systems have been developed using a high spatial resolution infrared thermal imager of resolution $320 \times 240$ pixels at 30FPS. It consists of an Uncooled Focal Plane Array (UFPA). In a research conducted by Martinelli et al. (Martinelli et al., 1999) the LCD displays a real-time infrared monochrome image. An aspheric mirror reflects the image from the LCD display onto the windscreen where it is viewable by the driver. A human can be detected at 500 metres and recognized at 135 metres. The video camera records the reflected image which appears black and white on the screen by a head up display (HUD) (DaimlerChrysler, 2000).

These sensors, and other sensors can be fused for tracking algorithms and to improve the reliability of the system. Scenario assessment is required to include most obvious road hazards and predictions. These night vision systems are expensive and an extra £10K has to be paid for installation in the car.

Similar systems have been developed using near infrared cameras and infrared LEDs by car manufacturers (DaimlerChrysler, 2000). These use infrared light to illuminate the road, which is invisible to the human eye. These infrared illuminated areas are then seen by cameras with near infrared capabilities. The mounting position of cameras is usually over the rear-view mirror.

Omron developed a high resolution CMOS camera that can see in low light and extreme lighting conditions such as tunnels, blinding sunlight and after dark (Oct 2003). This camera is a significant improvement over conventional CCD cameras and can detect images which are radiated with near infrared light.
**Occupant position sensor and driver measurement**

A 3D point measurement system has been developed for automobile drivers (Stockman *et al.*, 1997). The aim of this research is to measure posture for automobile seat design. Special markers are placed on the driver's body and these markers are focused by two cameras mounted inside a car. These cameras were calibrated and fixed at known distances to each other. By creating a stereoscopic vision the author was able to measure points on the human body in 3D space.

It is not necessary to find the exact measurements of the driver posture. Especially off-the-road driver measurements can mostly benefit designers and ergonomists in designing something safer. But on-the-road real-time occupant position sensors can give significant information that can be useful.

Some of the automotive manufacturers (Bruns, 2000, Breed *et al.*, Ghiardi, 1999) have started to manufacture occupant detection systems. These systems use load cells which are installed into the car seat to find the size and the height of the occupant. Manufacturing costs of these types of active safety systems will increase the cost of cars significantly.

**Anti-lock braking system (ABS)**

ABS was designed to give conditional control during an emergency stop or poor road conditions. ABS is now a standard option in cars. A typical ABS sensor includes a wheel speed sensor, electronic control unit and hydraulics unit. This becomes a closed loop circuit. The electronic unit checks and compares each wheel speed sensor. If the electronics control unit senses a lock up of any wheel it reduces the amount of pressure to the hydraulic unit at that wheel.
Electronic stability control (ESC)

Electronic stability control (ESC) is a term for a primary safety system in automobiles which is designed to improve vehicle handling. First developed by German automobile manufacturers, the ESC system compares the driver inputs from steering and braking. The ESC reduces excess power by the engine to stop understeer and oversteer by finding the lateral acceleration, individual wheel speeds. ESC also integrates traction control and ABS. ESC has different terms defined by each automobile manufacturer like electronic control unit, Vehicle Dynamic Control and Electronic Stability Program.

2.2.2. Secondary safety sensors

Airbags

First airbags started to roll out in the North American automobile market from 1982 by Mercedes Benz, a German automobile manufacturer. It consisted of a crash sensor, gas generator, airbag and knee bolster (Scholz et al., 2003). The first generation of airbags were more aggressive and caused injuries to the out of position, frail and older drivers. Second generation airbags (Figure 2-5) used less inflation power than the previous generation of airbags.
While doing a cost benefit analysis on airbags in 1994 (Fildes et al., 1994), comparison is made between the European standard and the American standard. European standard airbags have 40 litres capacity with a 24 km/hr firing range threshold, which is much smaller than the American standard airbag of 70 litre capacity with a 16km/hr firing range. The European airbag has a slower deployment rate than that of America and thus is less likely to injure an occupant. American standard full size airbag is more suited for unbelted occupants. The concept of harm reduction was introduced by Fildes et al. (Fildes et al., 1994) for quantifying these benefits. It quantified the unit cost, the frequency of a particular type of injury and the total cost of injury running into millions of dollars. This cost benefit analysis (CBA) was very useful for automotive manufacturers who are always keen to lower the risk and cost. The CBA showed that the American full size airbag has a ratio of 1.17, whereas the European standard airbag has a ratio of 0.98. This suggests that the American full sized airbag is beneficial to the occupant due to safety reason as well as car manufacturers.

The ultrasonic based occupant position sensor is a technology which allows the position sensor to be installed as a real-time system. It is developed by National Highway Transport Safety Administration, UK NHTSA (Breed et al.). This sensor system is made up of four ultrasonic sensors as shown in Figure 2-6. Ultrasonic
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sensors are able to find the driver position while driving. Pattern recognition in conjunction with neural network is applied to estimate the position and velocity of the occupant by the sensor. The sensor system is made to identify an empty seat, a baby car seat and other scenarios. It estimates the delay in the ultrasonic pulse which will help identify the position. The primary application of this position sensor is as an active feedback system for intelligent airbags.

![Ultrasonic sensors](Figure 2-6: Ultrasonic occupant position sensor)

A Side-Airbag safety electrostatic capacitive sensor was created by Hubbard et al. (Hubbard et al., 1999, Fukui et al., 2001). This sensor is installed on the inside of the car seat. The impression on the car seat can measure height, weight and size of occupant and inform of pattern. A pattern recognition algorithm is made to identify adults with different heights and to deploy a side airbag accordingly. The sensor is unable to give the position of the occupant. However position of occupant is crucial in some cases, therefore, it is difficult to show the effectiveness of this sensor unless the position of the occupant is predetermined.
Side airbags (SABs)

Side airbags (SABs) were introduced much more recently than conventional frontal airbags. The commercial vehicle manufacturers started incorporating SABs since 1996. SABs gives protection against side impact crashes to the occupants see Figure 2-7.

![Figure 2-7: Side curtain airbags deployed in crash test car (copyright Honda motors)](image)

2.2.3. Intelligent vehicle systems

Third aged drivers when turning at intersections are more likely to collide. Due to sudden encounters with pedestrians, traffic or on coming cars (Daimon et al., 2003). Third age driver behaviour in using Advanced Cruise-assist Highway system was monitored. Advanced Cruise-assist Highway system uses two way communications with other vehicles on the road using sensors. Experiments for this study were conducted on a driving simulator. Two scenarios selected involved making a right turn on a crossing and a pedestrian crossing. Both these scenarios are split into two experiments. Measurements taken during the experiment to study driver behaviour were coordinates, speed, time between oncoming vehicles when at an intersection and visual behaviour using 8mm video camera at 30FPS. The subject drivers were
then asked to make a right turn and to cross the pedestrian crossing when it was safe
to do so in the driving simulation. Third aged drivers collided 2.5 times more than
young drivers, which is significant. Another important parameter is the minimum
distance between cars when making a right turn without collision. This can be
classed as a near miss, and is more frequent in third age drivers than younger drivers.
This is due to slower reaction times in third age drivers. The visual information
confirmed that third aged drivers took longer for glancing at information than
younger drivers. For the younger drivers the reaction time for all tasks completed
was less than 3 seconds and 75% of tasks were completed in less than 1.5 seconds.
For third age drivers a few tasks took more than 3 seconds to complete. The majority
of tasks took over 2 seconds to complete.

2.2.4. Human and obstacle tracking

Human tracking technology used by many researchers is not completely novel or has
been used before using different techniques. Sensors such as placing load cells and
strain gauges on a car seat to find weight and position of the occupant, non-contact
sensors like CCD/CMOS cameras, infrared and ultrasonics to find driver’s height
and position in real-time have been used. Tracking using intelligent sensors is not
only limited to automobile passengers. Intelligent sensors are being used more and
more everyday to track human movements as well as other object tracking. Previous
research related to tracking using intelligent sensors is investigated in this section.

There are many kinds of detectors that are used for human information. Most
commonly used sensors are CCD cameras. These CCD cameras are high quality and
smaller in size but require a frame grabber card. CCD cameras with image
processing techniques are being used as human information systems. Application of
human information system are in Underground railway surveillance (Chow et al.,
2002), elevators for counting people (Schofield et al., 1997), tourist information
systems (Sacchi et al., 2001), face recognition and eye detection (Zhou et al., 2004).
Some researchers use camera images and develop novel algorithms using image-
processing techniques, while other research involves special kinds of sensor or marker based tracking during the experiment to track the human motion.

Recently tracking different objects, including rigid or non-rigid objects is one of the most active researches topics (Noyer et al., 2004, Tissainayagam et al., 2003). This object tracking also involves tracking humans. Most examples of human tracking are available using monocular image sequences (Noyer et al., 2004). For example accurate motion tracking of the human body using body markers (Figueroa et al., 2003), pedestrian tracking (Pai et al., 2004), or from surveillance cameras (Chow et al., 2002).

Human tracking is required in sports research for sport motion analysis. This is used as an entertainment, television, sports motion study and training guide for professional sportsman and medical research purposes (see Figure 2-8) (Chang et al., 1997). The software developed by the author uses video sequence from the sports scene. One video sequence shows tracking of a sportsman playing volleyball, Figure 2-8. From the video tracking it is possible to find information like the highest possible jump taken by the sportsman, the distance travelled and movement coordinates.

Figure 2-8: Tracking of a jump while playing volleyball (Chang and Lee, 1997)
Motion tracking is done by taking images from a camera and analysing those images in real-time or offline. Tracking of several objects is previously conducted, for example traffic tracking on a multilane express way for the purpose of safety and traffic management (Tai et al., 2004), human tracking to monitor their kinematics, identification and to study their motion for anthropometry data (Ning et al., 2004).

Some of the applications require more than just 2D motion information, they also require 3D information. 3D vision tracking is also important in virtual environments and computer animation applications. There are two types of 3D vision tracking. Monocular vision uses only one camera. Stereo vision uses multiple cameras. The multiple camera approach can extract 3D coordinates directly (Sun, 2004).

Another application of tracking is vehicle hazard and obstacle monitoring. A vision based real-time vehicle detection and recognition system was developed by Ran et al. (Ran et al., 1999). The sensor system includes a colour CCD camera mounted inside a vehicle pointing towards the road centre line. The video sequence is segmented and edge detected. This system used mainly as a lane departure system, can detect obstructions in the road. However the authors admitted that using CCD cameras will have problems with lighting and lane detection during night time.

Image or vision based scanning systems generally work at the speeds of 25 Hertz, 30 Hertz, 60 Hertz or better for the intelligent transport systems (ITS). This speed and distance cannot be achieved by sensors like laser range sensors, millimetre wave radar sensors and tactical and acoustics sensors. Vision based systems can also manage to work as lane tracking and obstruction tracking and detection systems. The only limitations that make vision based system less robust are during fog, snow, night or direct sun-shine conditions. Thus previously they have been replaced by millimetre radar sensors (Bertozzi et al., 2000). Infrared based imaging systems are able to use the flexibility and speed of vision based systems without having the limitations of a vision based system with an exception of detecting white lines or obstacles at ambient temperature. The infrared imaging systems can work poor weather conditions such as night, fog, snow and rain (Flir, 2006).
2.3. **Summary**

- Young drivers are at higher accident risk than any other age group, and the second most vulnerable age group for accidents is the third age drivers. However the third age driver accidents are more fatalities than injuries.

- Accidents risks include driver distraction, drink and drugs (DUID), sleepiness and other related symptoms.

- Third age driving problems include vision impairments like tunnel vision, reduction of visual field, not turning the head sufficiently, attentional abilities and memory and motor skills deficits leading to errors and lapses.

- Previous research shows that several intelligent sensors have been developed like pro-tension seat belts, radar sensors, ABS, ESC, intelligent airbags.

- Human tracking has been done previously for different applications like automated people counting, face recognition, traffic control, public transport surveillance, sports body motion. Most applications were vision based solutions.
3. Technical Background

3.1. Thermal imaging

All objects emit heat by three means: Conduction, convection and radiation.

1. Conduction, transfers heat through solid objects.

2. Convection, transfers heat through fluids like air and water.

3. Radiation, transfers heat through electromagnetic radiation.

Objects continuously radiate heat with a certain wavelength. This wavelength depends upon the temperature of the radiating object and its spectral emissivity. As the object temperature increases the radiation also increases. The radiation emitted also includes the infrared radiation emission of wavelength between 0.7 micro metres to 100 micro metres. Small ranges of infrared emission emitted by the objects are detected by the thermal imagers, which is then made visible as an image.

The concept behind the thermal imager infrared emission detection is the notion that the black body is a perfect radiator; it emits and absorbs all incident energy. The energy emission for the black body is the greatest possible energy emission for that certain temperature. Radiation power emitted by a black body as given by Plank’s radiation law is: (Burnay et al., 1988)
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\[ P(\lambda, T) = \frac{2\pi hc^2}{\lambda^2} \left\{ \exp \left( \frac{hc}{\lambda bT} \right) - 1 \right\}^{-1} \]  
(Equation 1)

where:
- \( p \) = Energy Radiated
- \( \lambda \) = Wavelength
- \( T \) = Temperature (Kelvin)
- \( h \) = Plank's Constant
- \( c \) = Velocity of light
- \( b \) = Boltzman Constant

Real objects are not perfect emitters or absorbers. Thus emissivity (\( \epsilon \)) of the real surface is defined as the ratio of thermal radiation emitted by a surface at a given temperature to that of a black body for the same temperature, spectral and directional conditions (Holst, 2000). Thus emissivity of a black body is 1 and all other real surface emissivities will be between 1 and 0. This electromagnetic spectrum range contains maximum radiative emissions, which are used for thermal imaging purposes (S.G.Burnay, 1988, 2000).

According to the Stefan Boltzman Law of emissivity radiation:

\[ w = \epsilon\eta T^4 \]  
(Equation 2)

where:
- \( w \) = Radiated energy
- \( \epsilon \) = emissivity
- \( \eta \) = Bolzmann Constant
- \( T \) = Temperature (Kelvin)
Infrared imagers are commercially available that measure infrared radiation. Infrared imagers are divided into five types based on the range of infrared radiation they can detect.

3.1.1. NIR (Near Infrared)

Detection wavelength range is 0.75 micrometre to 1.4 micrometre. These cameras are used for several applications, for example food quality control measures (Uddin et al., 2006), fibre optics in telecommunications, pharmaceuticals, analysis of chemicals and gasoline, and medicine for blood monitoring and imaging of materials including tissues (Ciurczak et al., 2002).

3.1.2. SWIR (Short wavelength Infrared)

Detection wavelength range is 1.4 micrometre to 3 micrometres. Applications include health and safety, surveillance, machine vision, night vision, and historical art inspection. They have much higher frame rates than LWIR and other infrared imagers and are thus recommended for machine vision applications.

3.1.3. MWIR (Medium wavelength Infrared)

Detection wavelength range is 3 micrometre to 8 micrometres. It is also called Intermediate Infrared (IIR). Applications for MWIR include process control, non-destructive testing, failure analysis, wildlife study, medical imaging, security and military use, maintenance and condition monitoring.

3.1.4. LWIR (Long wavelength Infrared)

Detection wavelength range is 8 micrometre to 15 micrometres. These types of infrared imagers are ideal for room temperature environments. This infrared imager
has expensive optics made from germanium, sapphire, or silicon. As LWIR is suitable for room temperatures human information sensors, people counters, surveillance equipment and military target applications are ideal applications. High end LWIR are expensive due to cryogenic cooling requirements, uncooled LWIR cameras are less expensive and use a micro-bolometer but have slower frame rates.

3.1.5. FIR (Far Infrared)

Detection wavelength range is 15 micrometre to 1000 micrometres.

3.2. Thermal imagers

Thermal imagers are infrared cameras with a detection range of 0.9 micrometre to 14 micrometre wavelength. Thermography converts thermal radiation into digital signals which converts it into a visible image. Thermographs are the image maps created by the thermal imagers.

There are two types of thermal imagers-cooled and un-cooled. Depending upon the application this selection is made. Un-cooled thermal imagers are most common and preferred as these thermal imagers are less expensive and require less power. They cover a spectrum range of 8 micrometres to 12 micrometres and stabilization time required by the thermal imager is insignificant, therefore output can be collected straightaway. The disadvantages of un-cooled thermal imagers include less sensitivity to temperature, and they work only for close distances.

3.2.1. Pyroelectric infrared detector

Pyroelectric (crystalline) materials produce charge when they undergo thermal change. When the infrared radiation strikes the pyroelectric detector a charge is produced. Pyroelectrics are not responsive to steady light input but react only to the change. Thus a physical shutter effect is required which is also termed a chopper. As
the pyroelectric detector only gives absolute temperature without the chopper the background temperature will disappear as pyroelectric devices only provide change in temperature (Miller, 1994).

![Typical PZT pyroelectric sensor schematic](Image)

Figure 3-1: Typical PZT pyroelectric sensor schematic (Schreiter et al., 2006)

Common pyroelectric detector materials are triglycine sulphate (TGS), lead zirconate titanate (PZT), PbTiO₃, LiTaO₃ and LiNbO₃.

### 3.2.2. IRISYS thermal imager

The IRISYS IRI1002 is a low resolution low-cost infrared thermal imager (Monarrez-Espino et al., 2006). The radiation detection range for this image is from 8 micrometre to 14 micrometres, thus classifying it as a long wave IR Imager (LWIR) (Al-Habaibeh et al., 2003). Temperature range for this infrared imager is -20°C to +90°C (with +150°C with reduced accuracy) with +/- 0.5°C error (Irisys, 2002). The original resolution of the imager is sixteen (16) pixels square but is usually interpolated for better visual analysis. The imager has a maximum frame rate of eight frames per second (8 FPS). The camera can be interfaced through RS-232C serial port to the PC. The frame rate can be changed by the writing commands to RS-232C port.
Thermograph acquisition from the IRISYS IRI1002 thermal imager has three modes:

1. Acquisition of single infrared frame from imager when command is written using serial port.

2. In this mode a specified number of thermographs are required at certain frame rate for a certain time period. This mode is useful but has a finite frame limit of 255. Therefore command needs to be present if more than 255 frames are required. It is worth mentioning that the time interval between two serial write commands cannot be set.

3. The third mode, when activated, sends thermographs at a specified frame rate continuously.

As the optics is concerned, the field of view is 20° degrees. For example if the infrared imager was to look at the area of interest from 1 metre centre distance, 0.352 metre square will be the viewable region. The focal length ‘f’ of the IRISYS imager is 17mm and the IRISYS IRI1002 is fitted with germanium lens.

The IRISYS IRI1002 focal plane array measures relative temperature therefore a mechanical chopper is necessary to make the ‘shutter open’ and ‘shutter close’. A frame by frame comparison creates a thermograph of stationary object. Without the mechanical chopper the stationary object in the field of view of the thermal imager will fade out into the background (Irisys, 2002).

### 3.2.3. IRISYS thermal imager construction

The IRISYS imager is packaged in an aluminium die-casting case of 100mm x 100mm x 60mm, with a weight of less than 1.3kg (see Figure 3-2). The power required is 12VDC at 300milliampere hours.
With the electronics and optics, currently packaged, the IRISYS package could be reduced up to 50mm x 50mm with 36mm thickness (approximately). The motor which is being used as a chopper is a considerable factor in increasing package size. The diameter of the chopper motor is 25mm with a length of 36mm a maximum speed of 240RPM. If the motor is reduced in size the packaging of the thermal imager can be reduced significantly.

### 3.3. Thermal imaging applications

The potential applications of thermal imaging are numerous. There are complete books devoted to the applications and their description of thermal imaging. Therefore only limited applications are listed from different areas of interest in Table 3-1.
<table>
<thead>
<tr>
<th>Applications</th>
<th>Area of interest</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gun sights/target</td>
<td>Military and paramilitary</td>
</tr>
<tr>
<td>Infrared search and track</td>
<td>Military and paramilitary</td>
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<tr>
<td>Military ground vehicle sensors</td>
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<td>Military space sensors</td>
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<td>Missile seekers</td>
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<tr>
<td>Tactical missile warning</td>
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<td>Perimeter surveillance</td>
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<td>Drug interdiction</td>
<td>Military and paramilitary</td>
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<td>Law enforcement</td>
<td>Military and paramilitary</td>
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<tr>
<td>Temperature distribution in wind tunnels for example temperature distribution on wings, missiles and fuselage</td>
<td>Industrial, inspection and monitoring (Aerospace/Military)</td>
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<tr>
<td>Rocket and jet engine diagnosis</td>
<td>Industrial, inspection and monitoring (Aerospace)</td>
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<tr>
<td>Shape and temperature distribution in exhaust plumes from aircraft jet engines</td>
<td>Industrial, inspection and monitoring (Aerospace)</td>
</tr>
<tr>
<td>Inspection of gas and fluid relief values</td>
<td>Industrial, inspection and monitoring (Petrochemical)</td>
</tr>
<tr>
<td>Detect faulty components in printed circuit boards</td>
<td>Industrial, inspection and monitoring (Electrical/electronics)</td>
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<tr>
<td>Breakdown of insulation on power lines</td>
<td>Industrial, inspection and monitoring (Electrical/electronics)</td>
</tr>
<tr>
<td>Monitoring of electrical switchgear applications</td>
<td>Industrial, inspection and monitoring (Electrical/electronics)</td>
</tr>
<tr>
<td>Monitoring of transformers and circuit breakers</td>
<td>Industrial, inspection and monitoring (Electrical/electronics)</td>
</tr>
<tr>
<td>Evaluating and inspecting furnaces / Refractory lining and its inspection for</td>
<td>Industrial, inspection and monitoring (Steel)</td>
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<tr>
<td>Cracks and Defects</td>
<td>Safety for Coal and Slag</td>
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<td>-------------------------------------------------------</td>
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<tr>
<td>Monitoring of bearing performance by measuring friction generated</td>
<td>Monitoring of bearing performance by measuring friction generated</td>
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<tr>
<td>Optimization of design of mechanical parts like improves design of belt and pulley to reduce energy loss</td>
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<tr>
<td>Checking plastic mould and die temperature distribution measurement &amp; check performance of pre-heated plastic samples</td>
<td>Checking plastic mould and die temperature distribution measurement &amp; check performance of pre-heated plastic samples</td>
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<tr>
<td>Night vision system for commercial vehicles</td>
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<tr>
<td>Inspection of electrically heated car windows</td>
<td>Inspection of electrically heated car windows</td>
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<td>Thermography is used to study moisture non-uniformities in the paper manufacturing process</td>
<td>Thermography is used to study moisture non-uniformities in the paper manufacturing process</td>
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<td>Inspection of heat exchangers</td>
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<td>Inspection of process plants</td>
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<td>Inspection of electrically heated windows</td>
<td>Inspection of electrically heated windows</td>
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<td>Investigation of vascular disorders</td>
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<td>Oncological investigations</td>
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<td>Investigation of pain, trauma and inflammatory conditions</td>
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Industrial, inspection and monitoring (Steel)

Industrial, inspection and monitoring (Mechanical)

Industrial, inspection and monitoring (Manufacturing)

Industrial, inspection and monitoring (Automotive)

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Industrial, inspection and monitoring (Manufactoring)
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<table>
<thead>
<tr>
<th>Earth observing sensors</th>
<th>Astronomy, metrology and geo</th>
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<td>Interplanetary space sensors</td>
<td>Astronomy, metrology and geo</td>
</tr>
<tr>
<td>Weather instruments and cameras</td>
<td>Astronomy, metrology and geo</td>
</tr>
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<td>Oil pollution control and oil spill</td>
<td>Various</td>
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<tr>
<td>Endangered species monitoring</td>
<td>Various</td>
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<tr>
<td>Night vision for commercial airlines and shipping</td>
<td>Various</td>
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<tr>
<td>Study isotherm patterns of welding</td>
<td>Various</td>
</tr>
<tr>
<td>Testing of tyres and temperature profile measurement across tyres</td>
<td>Various</td>
</tr>
<tr>
<td>Fire brigades to see through smoke, mists and evacuation purposes</td>
<td>Various</td>
</tr>
</tbody>
</table>

Table 3-1 Applications of thermal imaging (Burnay et al., 1988, Holst, 2000)

Use of thermal imaging in the automotive research industry has improved in the last few years. Night vision HUDs are being installed in high end commercial vehicles to see ahead in night and poor visibility conditions (Martinelli et al., 1999). High cost thermal imagers are also used for designing a climate control system in automobiles. A study was conducted by Ghiardi (Ghiardi, 1999) in which a high spatial resolution thermal imager is focused on the face of the driver. Several scenarios were conducted in which a driver got in the car fitted with thermal imager. These scenarios vary from hot sunny weather to cold rainy weather. An automated climate control system linked with the thermal imager measured heat patterns from the driver’s face and monitored driver condition over time inside the car. More automotive applications using thermal imaging are discussed in the night vision sensor section 2.2.1 and thermal human tracking section 2.2.4.

Infrared imaging can aid in the study of geology. For example finding a rise in sea temperatures, levels of desertification on land, finding clouds and other geographical features using satellite imagery. Thermal imaging provides a significant advantage
by removing the limitation of day and night, thus land, sea and clouds can readily be identified. Metrological satellites are being used for detecting clouds and their patterns to study and forecast weather (Pergola et al., 2004, Fisher et al., 2004).

Medical thermography is an actively researched topic. At an ambient temperature an unclothed healthy person has a temperature of 35 degrees over the chest region whereas 25 degrees over the feet.

1. Skin surface temperature is based on determination of age of a person. The warmest temperature is near the head and trunk.

2. The surrounding temperatures have a significant effect on the human body.

3. During exercise the temperature of the human body increase up to 40 degrees without any illness. But monitoring during exercise the excessive heat is generated by the active muscles. For example running produces heating effects in legs.

4. Obesity modifies the temperature distribution. Different thermal patterns are created in the obese. The fatty areas are the cold regions which modify the expected heat pattern shown by non-obese people.

3.3.1. Thermal imagers for human tracking

There has been a growing need for detecting and tracking human bodies using non-contact methods in the field of air-conditioning, lighting, security and others. But human information is difficult to process if only visual sensing is used, as the lighting variations give a major challenge making visual cameras inadequate for processing human movements. Infrared imagers tend to simplify this imaging problem. The advantage of infrared cameras over visual is their use in night time and bad weather conditions.
Infrared tracking is not very common, as many applications require high spatial resolution infrared cameras which are expensive (Reynolds et al., 2002). Thus due to this reason Infrared target tracking is vastly used in air defence applications only (Yilmaz et al., 2003, Tidrow et al., 2001).

A journal paper by Eveland et al. (Eveland et al., 2003) describes research on detection and tracking of faces using a thermal imager. For the purpose of thermograph segmentation the author classified scenes into exposed skin, covered skin (with clothes, hair etc) and background. After modelling the skin into thermal scenes the author was able to calculate the probability of exposed skin and covered skin in the scenes. The author used MWIR and LWIR high spatial resolution thermal imagers for indoor and outdoor detection and tracking of subjects.

Human observation or human information sensors are actively using thermal imagers. Research conducted by Armitage et al. (2004) used IRISYS thermal imagers for tracking and counting people. The author argues that using low resolution low cost IRISYS thermal imager is the preferred choice over visual and high resolution thermal imagers as it works in any lighting conditions as well as being low in cost. A very simplistic approach is used by (Chamberlain et al., 2004). Two people counters are installed which are capable of acquiring 16x16 pixel thermographs. By using two people counters it is possible to get sub pixel accuracy for the centroid of the targets.

Another pedestrian monitoring sensor developed by Armitage et al. (2005) provided a working area of 10 square metres. This was an improvement on the previous sensor mentioned in Chamberlain et al., (2004), but real time. The author argues that the techniques used by infrared imagers are significantly different from visual sensors due to the thermographs involved. The research used two thermal imagers, IRISYS and FLIR, with a resolution of 16 square pixels and 256 square pixels respectively (see Figure 3-3). The later thermal imager is used to segment the thermographs into regions by differentiating between background and people.
An occupant detection sensor was developed by Morinaka et al. (Morinaka et al., 1998). This occupant detection and movement sensor consists of two parts, an upper part which is a distance sensor and a lower part which is a pyroelectric infrared detector made using PBTiO$_3$. The pyroelectric infrared detector consists of a spherical lens and chopper mechanism which is connected to a brushless motor, the resolution achieved by interpolation was 48 pixels by 180 pixels. The distance was measured by a four channel distance sensor consisting of near infrared LEDs transmitter. The experiments were conducted in 5 metres by 6 metres area. The detection algorithm is based on simple fuzzy logic. However these IR imagers are very expensive and thus low-resolution low-cost IR imagers are developed for this purpose. These IR imagers are un-cooled with a mechanical chopper, which is inserted in front of the detector. Further research on a similar sensor design is discussed and used by Hashimoto et al. (Hashimoto et al., 2000) and Yoshiike et al. (Yoshiike et al., 1999).

Other smaller applications of infrared imagers include using it as a night vision device for tracking and detection of animals, termites and insects (Reynolds et al., 2002).
A medium-resolution infrared imager (64 x 64 pixels) was also developed for position tracking of occupants for an intelligent airbag system (Qinetiq, 2004) as shown in Figure 3-4. This sensor developed by BAE system’s sister company ‘Qinteq’ in collaboration with First Technologies shown in Figure 3-4 named the ‘Fungi Thermal Imager’.

3.4. Infrared & Visual Image Acquisition software

I-Quire software, as shown in Figure 3-5, is used which was developed by the author for the infrared and visual image acquisition. This software acquires webcam images and thermal imager in soft real-time. The image frequency in the experiment is set at 2FPS. This image acquisition frequency is selected on the basis of the length of experiment and reaction time of each volunteer. The image acquisition is done for the whole length of the simulation scenario. This software is modified extensively for the experiment to take an unlimited number of images during the experiment, see section 7.2.4.
3.5. Talley pressure matrix

A Talley pressure monitor is manufactured by Talley Medical for the pressure monitoring which is used as a design tool for different products and experiments. It is used to estimate the weight of the occupant. Also the pressure monitor is helpful in finding the position of the occupant as it finds the pressure of small air pockets. The pressure monitor is connected through RS-232C port from the IBM-PC. The specifications of the Talley pressure monitor are shown in Table 3-2.
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<table>
<thead>
<tr>
<th>Number of air matrix</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total number of air pockets</td>
<td>8x12 (96)</td>
</tr>
<tr>
<td>Communication</td>
<td>RS-232C</td>
</tr>
<tr>
<td>Throughput</td>
<td>9600bps</td>
</tr>
<tr>
<td>Parity</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 3-2 Talley pressure monitor specifications

Figure 3-6 Talley Pressure monitor set-up on driving seat; V-shaped to correspond to driver legs position
The raw data is read into MatLAB. The data is then arranged into a realistic V-shape as arranged onto the driving seat shown in Figure 3-6. The measurements of the driving seat are also taken into account. Figure 3-7 shows the control unit of the Talley pressure monitor. The resulting surface received from the Talley pressure monitor while driving is shown in Figure 3-8. The whiter the surface the higher the weight, while black shows no weight.
The pressure mat has 96 air pockets, which are used to measure the pressure and is connected to the Talley pressure monitor which pumps the air and measure it. The values are then output through RS-232C port and stored in ASCII format.

3.6. Visual camera

The main purpose of using a webcam during the experiment was to compare and verify the results. Visual images provide plenty of information. It can be used to validate infrared imager thermographs. Using a webcam instead of a high-resolution visual camera allowed the experiment to be conducted at extremely low costs.
3.7. Driving simulator

To simulate the driving in a laboratory without risking safety a low cost driving simulator was used for the experiments. The STI Driving Simulator (STISIM) by Systems Technology, Inc is most suitable for research purposes. It is one of the most stable driving simulation packages around with 40 years of development (Noy et al., 2004).

The simulation is created using complete vehicle dynamics model in real-time (Wade Allen et al., 1998). This vehicle model was developed for the National Highway Traffic Safety Administration. STISIM contains a GAINS file. This file contains several parameters of vehicle dynamics and visual display transport. For the STISIM release used, sixty-three (63) parameters are given in the GAINS file. From that you can set the control to response relation of steering wheel input, lateral and directional motions and their relationship with throttle and brake. The vehicle dynamics model contains a steering module, which inputs the steering values calculating the vehicle path curvature. A speed control module inputs throttle and brake. The speed feeds into the steering control module. To calculate engine RPM transmission gear ratio is used.

3.7.1. Construction of Ford Scorpio test rig

The hardware and software (see Section 7.2.2) was supplied by STISIM, and installed in a static Ford Scorpio car, Figure 7-1. The car is controlled by force feedback steering column, accelerator and brake. The steering, brake, accelerator and speedometer are connected to absolute encoders, which give analogue readings to the Data Acquisition Card (DAC). This DAC is connected and configured with a PC with an installed copy of STI Driving Simulator. The DAC board is from CIO-
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DAS08/JR series from Measurement computing Inc and has a capacity of 8 analogue and 8 digital I/O channels (Measurement-Computing, 2001).

The animated driving scene was projected onto a wall, which is 5 metres by 5 metres and 5 metres (approx.) away from the driver's position. The software then projects 135 degrees field of view of scenario on the wall.

The later set-up was in a custom made rig constructed by ESRI (Ergonomics and Safety Research Institute), which can be adjusted to accommodate 5th to 95th percentile range of users. The steering force feedback column and pedals is taken from a Range-Rover.

3.7.2. Programming scenarios

Driving tasks and scenarios are defined using a command list of events called simple scenarios definition language (SDL). The simulation, while running, can collect and store various parameters. Speed, vehicle curvature, road curvature, vehicle heading angle, lateral lane position, distance travelled, steering angle, throttle input, brake input, time, signal indicators and use input based signals can be collected and used for offline data analysis (Rosenthal et al., 1999). The build 1.1.15 for STISIM used in the experiments gives 50 command list events, which can be programmed into simulation scenarios.

3.8. Artificial intelligence and Image processing techniques

Digital image processing is currently a very active field of research. Humans have the ability to analyse and act according to visual information, an ability which is quite remarkable and unnoticed by humans. To make a machine do the visual
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analysis and act accordingly is a challenging task. As images taken, visualized by humans and photographed has now taken a complete turn. Now the images are captured, manipulated and action which is derived from them is made through computers. Great technological advances have been made to visualize these images from the eye of machines over the years. This has opened many areas of new research and merged many engineering disciplines (Jahne, 1999).

Further work is done in particular areas to make the computers more intelligent for analysing the visual information provided. Now they are able to predict and scan information almost like humans do. For example, object recognition such as distinguishing between different kinds of fruits, or maintenance of rail fasteners (Mazzeo et al., 2004).

In biometrics, the human face (Zhao et al., 2004, Turk et al., 1991) or finger print recognition is routinely carried out. Use of artificial intelligence and digital image processing in medicine (Wu, 2004), traffic control and management (de la Escalera et al., 2003) and automated target recognition is well developed (Pasquariello et al., 1998).

The most commonly used techniques in computer vision artificial intelligence are:

1. Fuzzy Logic

2. Artificial Neural Networks
   a. Backpropagation neural network
   b. Radial basis neural network

3.8.1. Fuzzy logic

Fuzzy logic is a mathematical technique for dealing with imprecise data and problems. The fuzzy logic system makes only true and false (if-else) decisions based
on rule sets. This system resembles human logic and is a kind of artificial intelligence.

More information about fuzzy logic based system can be taken from Harris (Harris, 2000, Timothy, 2004)

3.8.2. Neural networks

Artificial Neural networks (ANN) (Haykin, 1999) are mathematical models that resemble the biological method of human decision making processes by using neurons which are interconnected to each other (Lee, 2004). The ANN decision accuracy depends upon the following two factors:

- The learning process: The training method is different for each type of neural network. The supervised and unsupervised learning are the most common techniques and will be discussed below.

- An ANN stores information in the form of interconnection strengths between neurons and the synaptic weight of each neuron.

Artificial neural networks are collections of mathematical models that emulate some of the observed properties of biological nervous systems and draw on the analogies of adaptive biological learning. The ANN has a novel architecture that mainly contains highly interconnected neurons. These neurons contain the activation functions like 'linear', 'sigmoid', 'logarithmic', 'tangential' and so on, depending upon the particular application of where the ANN is used.

The main advantage of using neural networks is the full automation of the learning and classification processes. Therefore, they can be implemented in fully automated monitoring systems, such as people counting to recognize and classify different
patterns without human involvement, thereby, eliminating any error or lapses associated with human concentration during a repetitive task.

As in nature, the network function is determined largely by the connections between elements. Some Neural networks are classified as feed-forward while others have a different architecture like self-organized or supervised network, RAM based neural network, Radial Basis Neural Network (RBN). The selection of ANN, training technique and activation function used depends upon the type of data that is being processed (Ramadan et al., 2004).

**Supervised Learning**

During supervised learning of an ANN, an input stimulus is applied that results in an output response. Then this response is compared with a desired output i.e. the target response. If the actual response differs from the target response, the neural network generates an error signal, a popular measure of the error $E$ for a single training pattern, is the sum of square differences i.e.

$$E = \frac{1}{2} \sum_i (t_i - y_i)^2$$

(Equation 3)

Where,

$t_i$ = desired or target response for $i$th unit,

$y_i$ = actually produced response for $i$th unit.

$E$ = Error calculated for adjustment of synaptic weights

The error "E" is then used to calculate the adjustment that should be made to the network’s synaptic weights so that the actual output matches the target output.
Unsupervised learning

Unsupervised learning does not require a target output. It is usually found in the context of recurrent and competitive nets. In case of unsupervised learning, there is no separation of the training set into input and output pairs during the training session, the neural net receives as its input many different excitations, or input patterns, and it arbitrarily organizes the patterns into categories. When a stimulus is later applied, the neural net provides an output response indicating the class to which the stimulus belongs. If a class cannot be found for the input stimulus, a new class is generated. However, it should be noted that even though unsupervised learning does not require a teacher, it requires guidelines to determine how it will form groups. Grouping may be based on shape, colour, or material consistency or on some other property of the object.

Back Propagation Neural Network

Back Propagation Neural Networks (refer Figure 3-9), are one of the most commonly used neural network structures, as they are simple and effective, and have been used successfully for a wide variety of applications, such as speech or voice recognition, image pattern recognition, medical diagnosis, and automatic controls.
It is a supervised neural network, which consists of "n" numbers of neurons connected together to form an input layer, hidden layers and an output layer. The input and output layers serve as nodes to buffer input and output for the model, respectively, and the hidden layer serves to provide a means for input relations to be represented in the output. Before any data has been run through the network, the weights for the nodes are randomly chosen, which makes the network very much like a newborn's brain, developed but without knowledge. When presented with an input pattern, each input node takes the value of the corresponding attribute in the input pattern. These values are then "fired", at which time each node in the hidden layer multiplies each attribute value by a weight and adds them together. If this is above the node's threshold value, it fires a value of "1"; otherwise it fires a value of "0". The same process is repeated in the output layer with the values from the hidden layer, and if the threshold value is exceeded, the input pattern is given the classification. Once a classification has been given; it is compared to the actual, i.e. desired classification, and the error is fed back (back propagated) to the neural network and used to adjust the weights such that the error decreases with each iteration and the neural model gets closer and closer to producing the desired output (Ince, 2004, Ramadan et al., 2004, Marengo et al., 2004). This process is known as
"training". The back propagation neural network used in this study uses a sigmoid function in the hidden layer and a linear function in the output layer.

**Radial basis neural network**

A typical radial basis function (RBF) network is a three-layer network: a layer of input neurons feeding the input vectors into the network; a single hidden layer of RBF neurons calculating the outcome of the basis functions; and a layer of output neurons calculating a linear combination of the basis function. The number of input neurons should be the same as the number of input variables.

RBF networks are often used to solve problems of supervised learning. Supervised learning is to guess or estimate a function from some example of input–output pairs, with little or no knowledge of the form of the function. The function is learned from the samples that a teacher supplies. The training set contains elements that consist of paired values of the input and the output. The function relation between the input \((x)\) and output \((y)\) is given by \(y = f(x)\), where \(x\) is a vector and \(y\) is a scalar. The units in the input layer do not process the information, and they only distribute the input variables to the hidden layer. Thus, the RBF network can also be considered as a two-layer network.

RBF neural networks can offer approximation capabilities similar to those of the multi-layer perceptrons which are basic components of BPN. In general, the radial basis function method is a global interpolation technique that has good localization properties (Erfanian Omidvar, 2004), as it avoids the difficulty of local optima by conducting the training procedure in two steps. The locations of the centre vectors are found in the first step; then the values of the weights are optimized in the second step. Therefore, it provides a smooth interpolation of scattered data in arbitrary dimensions. It has been proven (Park et al., 1991, Park et al., 1993) that radial basis neural networks with one hidden layer are capable of universal approximation. Radial basis neural networks can be summarized as follows (Morelli et al., 2004):
\[ f(\tilde{v}_i) = \sum_{i=1}^{j} q_i \sigma_i [\|\tilde{v}_i - \tilde{u}_i\|] + p(\tilde{v}_i) \]

where,
\[ \tilde{u}_i = \text{centre of activation functions} \]
\[ q_i = \text{parameter for optimization} \quad \text{(Equation 4)} \]
\[ p(\tilde{v}_i) = \text{polynomial} \]
\[ \sigma = \text{activation function} \]
\[ j = \text{number of neurons} \]

RBF neural networks have widely been applied to problems of supervised learning, such as regression (Li et al., 2004, Loukas, 2001) and pattern recognition (Haddadnia et al., 2003).

### 3.9. Summary

- Heat is transferred by three means: conduction, convection and radiation. Thermal imaging can detect heat that travels by means of radiation. Thermal imagers are used to acquire this radiation data in the form of thermographs.

- Thermal imagers are classified based on their temperature measuring range. Discussed in detail is the IRISYS thermal imager which is a 16x16 array low resolution thermal imager available at a low cost. It is classified as a LWIR thermal imager which communicates to an IBM PC using RS-232c port. Human information sensor and other room temperature applications are based on LWIR type IR imagers.

- Software is developed as a data acquisition platform using National Instruments Lab/Windows platform. It acquires, organises and stores IR and visual data.
• This chapter also discusses briefly the tools that will be used during the experimentation like the STISIM driving simulator, visual camera and Talley pressure monitor.

• Types of artificial intelligence are discussed. Working of most common types of neural networks i.e. BPN and RBN is explained.
4. Hypothesis

4.1. Hypothesis

The information provided by low resolution infrared imaging can be used as the basis for a system which can reduce the risks to 3rd age and similarly impaired drivers.

4.2. Research question

Research questions form the basis on which research is planned and conducted. Every research programme has a hypothesis or a main research question. This chapter deals with the main research question and secondary research questions.

• How may we identify driver postures, movements and behaviours which pose a high level of risk?

4.2.1. Secondary research questions

• How to create a low cost safety system which would be non-contact and non-intrusive?

• How can low resolution infrared imaging be used to find driver's movement while driving?

• Can restriction of movement be found in the third age and impaired drivers?
• Can the system locate 'out of position' drivers?

• Can the system detect periods with eyes off the road?

• Can the system identify drowsy drivers? What can be done to identify signs of drowsiness while driving?

• What can be done to make cars safer by considering the driver's height/ head height?

• How can driving be made safer for third age drivers in the future by using this system?

The main focus of this research would be on the third age drivers. However, this does not mean that the proposed safety system is any less useful to other drivers.

4.3. Detailed research layout

Developing an AI (Artificial Intelligence) based thermographic imaging algorithm (AITI) and conducting experiments to verify it are interrelated activities. This is due to the complexity of the process involved in designing an AITI algorithm. Therefore a research layout is first defined which helps in developing the AITI.

The research programme layout (Figure 4-1) is different from the methodology given in Chapter 1. The methodology provides a 'bird's eye view' of the research whereas the research layout defines how the technical work will be conducted and relates to Stage 2 of the methodology (Figure 1-2).
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Figure 4-1 Flowchart of research programme
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The research programme is divided into four sections, which are:

1. IR position tracking
2. Behaviour Modeller
3. Driver task analysis
4. Integration

The first section of the research layout helps to identify the limitations and behaviour of the IRISYS infrared imager. This section will have series of smaller experiments and will help find an optimal method for tracking driver movement using thermographic imaging. Each imaging technique will be verified and validated with experiments, making it an iterative route. The position of the IRISYS thermal imager is also very crucial and its optimal location will be found in this stage.

A behaviour modeller will be the core section for the development of the AITI algorithm. A neural network will be designed that will use successful techniques of thermographic imaging from the previous section. Alternatives to neural network are fuzzy logic, hybrid intelligence and Bayesian network. The main decision systems are fuzzy logic and neural networks. A comparison of fuzzy logic systems and neural networks and why neural networks are preferred over fuzzy logic for this application are discussed in section 6.1 and section 6.2. A well laid out experiment will be conducted on a driving simulator to validate the AITI algorithm. Validated results from the experiment will also be compared with real life video driving data.

Another experiment will be conducted with a wider range of subjects. Data from the experiment will be analysed by the AITI algorithm developed in behaviour modeller. The third section will also answer the research questions made earlier in this chapter. It will further discuss the results and scenarios in which the system will be useful. The ‘integration’ section will look briefly into the future research work for this system and integration of this system in vehicles.
4.4. Hypothesis validation

The research will aim to provide validation that the proposed system can track driver postures, movements and aspects of behaviour which might affect safety.

4.5. Summary

- A hypothesis and primary research question are provided, aimed at determining how to identify driver movements and postures which pose a high level risk. Other secondary questions are also stated which are related to the primary research question.

- An AITI algorithm will be developed and experimentation will be conducted to evaluate the results of the algorithm. This research is laid out in four stages.

- The safety system will deliver driver posture detection at the end of the research.
5. Imaging techniques and Image Processing Algorithms

This chapter is divided into two main sections. The first section discusses the imaging techniques or special techniques developed and subsequently used in the image processing algorithm. The second describes the actual development of the image processing algorithm.

5.1. Imaging techniques

The following sub-section describes the imaging techniques used in the development of an imaging algorithm or the concepts of imaging which are useful in the understanding.

Infrared imaging is mainly a temperature measurement system. Previously the primary application for infrared imaging was in the field of defence and military but since the introduction of low resolution infrared imagers with lower cost applications commercial and industrial solutions are being developed and researched. Infrared imaging is superior to visual systems for tracking or monitoring human and other living beings as it seeks heat from the body. In an automobile safety context infrared imaging is used in applications such as minimizing night hazards, and improved visibility in poor weather conditions, especially in fog, rain and snow.
5.1.1. Difference between visual image and infrared thermograph

A true digital colour image is a 24-bit image. Each pixel value in this image is specified by 3 values which are red, green and blue in a true colour image. A true colour image does not use a colour map, the pixel colour and intensity is calculated by the combination of these three values, whereas a greyscale image is only 8 bit as there is only one bit-value for each pixel. A colour map is required to render a greyscale image; it consists of different intensities of grey against each pixel value. In other words a greyscale image pixel value is equal to the average of three values of each pixel in a true colour image.

The difference between a greyscale image and infrared thermograph is its pixel value. In an infrared image the intensity value of a pixel is replaced with the temperature; see Figure 5-1. An infrared thermograph can be considered as an 8-bit temperature map. For example, consider an infrared image with greyscale infrared thermograph, the higher the temperature the whiter (hotter) the pixel.

![Figure 5-1: Differences between infrared and visual image](image-url)
5.1.2. **Infrared Image Interpolation**

An interpolation process estimates values of intermediate components of continuous function in discrete samples. Interpolation is extensively used in image processing to increase or decrease the image size. There are commonly five types of interpolation used cubic, spline, nearest, bilinear and hyper-surface (Kulkarni, 1994).

An interpolation technique does not add extra information into the image but can provide better thermal images for human perception. For bicubic interpolation, the output pixel value is the weighted average of the pixels in the nearest 4 x 4 neighbourhood. Mathematically, bicubic interpolation can be described as follows:

The Lagrange polynomial interpolation:

\[
P(q) = \sum_{i=0}^{3} f_i L_i(q) \quad \text{(Equation 5)}
\]

(Al-Habaibeh *et al.*, 2003)

Where,

- \(q\) = Point at which interpolation takes place
- \(P(q)\) = interpolated value
- \(f_i\) = Known values on the grid at points \((q_i)\)
- \(L_i(q)\) = Lagrange polynomial, for example

\[
L_i(q) = \prod_{k=0}^{3} (q - q_k) / (q_i - q_k)
\]

The infrared images taken from the infrared imager require interpolation. The interpolation is required mostly for recognition of features by the human eye as the 16 x 16 pixel image as shown in Figure 5-2 does not give enough visual information. The linear and spline interpolation are better interpolated functions but due to
computation complexities and time taken by the spline interpolation the linear interpolation is preferred as it is the simplest type of interpolation. A single infrared image, as shown in Figure 5-2, with all four types of interpolation in a greyscale colormap.

![Interpolation Methods](image)

**Figure 5-2: Four types of interpolated infrared images**

### 5.1.3. Multiple level segmentation

The linear and spline infrared interpolated image also provides more image area. The next stage is to reduce the linearly interpolated image into 4 ranges of temperature as shown in Figure 5-3.

Based on principals discussed in the above paragraph and also discussed by Eveland *et al.* (Eveland *et al.*, 2003); 100 images were taken of the volunteers. All of these readings are taken after volunteers had been in room temperature for more than 15 minutes. Room temperature ranged from 19 to 21 degree Celsius. Before going further the difference between visual and infrared images is discussed in the following paragraph.
Thus these 100 infrared images are interpolated to obtain a bigger visual image. Using the mean of reference infrared images the room temperature is calculated. Reference infrared images are created by taking samples of images without any subject in the image field of view. During these experiments room temperature value was from 18.5 to 20.5 Degree Celsius. Thus any values from 18.5 to 20.5 are assigned to the background layer. Going further, after analysing these infrared samples with visual images four more layers are assigned to the infrared image. These layers are as follows:

1. Covered skin: this area of infrared includes covered skin, mostly can be covered with cloths.

2. Hair and skin: The second layer is assigned to hair, hands and areas other than the face.
3. Face area: the third and most important layer is the face layer. This mostly focuses on the area of the face. This temperature range will be used in the first part of image processing.

4. Face feature: This range being warmer than everything else, focusing on the mouth and nose region. Sometimes it also focuses on the forehead depending upon the density of hair on the forehead.

This classification of infrared temperature range is suitable for volunteers who are working in normal conditions at room temperature of 21 degree Celsius. Thus after classification at different temperature the multiple layer segmentation is shown in Figure 5-4. The segmentation was done with the face features being the warmest region, then the face region temperature, followed by uncovered skin regions. The covered body background separation is from the cold background which was around 21 degrees Celsius at the time of the experiment. The final interpolated image is inverted to aid visualization.
Figure 5-4: shows multiple layer thresholding on Infrared image showing a person driving a vehicle.

From the above segmented binary images it can be seen that different features can be extracted using subtraction of images.

The most important feature that can be found using this image processing technique is the face contours separation, as shown in Figure 5-4. Using this segmentation algorithm the face contours like cheek structure or hairstyle is prominent in this image (Figure 5-5). Thus face contours of each volunteer infrared image are extracted. All volunteers are looking forward at that moment.
The use of computer based imaging analysis is a good alternative to visual identification. Researchers have been using image feature analysis to classify and identify different groups of objects. For example in food sciences researchers have classified wheat grains based on their colour and sizes, and frozen pizza toppings inspection before being packaged. In medicine and laboratory counting and classifying micro-organisms is carried out based on their features like size and shape.

In the field of transport and vehicle safety the detection of pedestrians and obstacles using non-stereo and stereo vision in visual and night vision cameras, road curvature recognition based on road markers, driver assistance systems and autonomous vehicle navigation have been achieved (Mar et al., 2003 and Bertozzi et al., 2000). In the field of human behaviour and ergonomics study the tracking of driver or athlete behaviours using visual markers on their body is a common technique. In the field of defence and military human and vehicle tracking and recognition, target tracking uses infrared imagery. The list of work done in the field of imaging is vast and only a glance is what is achievable is discussed above.
5.1.4. Imaging features extraction

Information in images can be classified using image processing features. Classification of information in images is done by extracting different features from the image. Details of extracting imaging features are discussed in Section 6.2.1 under the heading of "Scatter-gram selection method neural network input vectors".

5.1.5. Image processing analysis tool: CompareIQ2

CompareIQ2 as shown in Figure 5-6 is a standard GUI interface for MatLab for the I-Quire software (image acquisition software used in the experiment). Further details for I-Quire are available in Amin (Amin, 2003). CompareIQ2 is used to analyse the experimental data visually and export certain visual and infrared images in MatLab. This program is a basic platform for the image processing techniques used. It consists of two windows showing a visual image and the corresponding Infrared image.
This GUI interface for MatLAB has proved to be really useful for running analysis on hundreds of images through the experiment and analysing their results. The infrared image or image processing technique applied is placed in that certain plot and then applied sequentially to all infrared images.
5.2. Image processing algorithm

5.2.1. Phase 1: Imaging algorithm initial development

The initial algorithm which was designed had two stages: pre-processing and processing. Each block of the imaging algorithms is discussed individually (Figure 5-7).

Pre-processing

Reading Infrared thermograph
Interpolation

Processing

Multiple level Segmentation
Feature extraction
Tracking plot

Figure 5-7: Preliminary phase imaging algorithm

Pre processing

Pre processing is an important part of an image processing algorithm. It helps the image processing algorithm by reducing the noise and applies any other image enhancing processes. The infrared thermographs which are acquired from the infrared camera contain negligible amount of noise. This is due to the unconventional imaging mechanism and the germanium lens.
Reading the Infrared thermograph

Infrared thermograph acquisition is conducted by using a RS-232C serial port communication. Further details of infrared acquisition can be found in Chapter: 7. The acquired infrared thermographs are stored on the hard disk. MatLAB reads the infrared protocol stored on the hard disk by the software and interprets it into a visual representation of infrared thermographs (see Appendix B).

Interpolation

The raw infrared thermograph is 16x16 pixels. Interpolation is required to get a better visual representation and larger area to work on. Infrared data interpolation is done to achieve 128 x 128 pixels image height and width.

Interpolation is further described in detail in the Imaging Techniques section, Chapter 7.

Processing

The processing of the initial algorithm contains three stages; segmentation of infrared image, extraction of features from the segmented image and track plot of the driver using those features. These stages are described in detail in the following subsections:
Multi level infrared segmentation

The Infrared thermograph histogram, (shown in Figure 5-8) displays three peaks in which two peaks are distinct, the large peak on the left shows the background which has less temperature and is represented in black.

![Interpolated infrared image with histogram](image)

Figure 5-8: Interpolated infrared image with histogram

The other peak which is approximately in the centre and covers a greater area than the background peak is the uncovered and clothed part of the subject shown in the infrared image (see Figure 5-9).
The third peak on the extreme right represents the hottest region in the infrared image. This region is the face; a line is drawn in Figure 5-10 showing the position of face segmented infrared image.
Feature extraction

After segmentation of the infrared image comes the stage of extracting features. See section 6.2.1, "Scatter-gram selection method neural network input vectors" for more detail.

Tracking plot

Software is written in MatLAB that can track movement of the volunteers while driving as shown in Figure 5-11. The thresholded infrared image is that of a subject...
driving, whereas the plots in the right window show the movement of the head within the field of view of the infrared imager, which is 355x355 sq millimetres.

The centre position of the head is used for plotting coordinates. This can be seen taking a closer look on plots as in Figure 5-12. Label (A) in Figure 5-12 shows the ideal position of driving. But when the subject comes onto position (A), he puts on a seat belt and follows path (B) which is traced in Figure 5-12. During driving the subject comes to a stop (in this particular scenario), rolls down a window, swipes the card to simulate barrier exit. This motion can be seen from the plot of path (C) in Figure 5-12.
5.2.2. Phase 2: Advanced approach – Angled IR

The previous algorithm has some drawbacks. These drawbacks are listed as follows:

- Mounting position of the IR camera. It blocks the viewing area of the driver.
- It is only possible to track the driver, no identification of driver posture.

Therefore a new imaging algorithm was developed to eliminate the deficiencies of the previous algorithm. Figure 5-13 shows the previous position of the IR imager, in which the camera was mounted in line with the steering column and the mounting height was equal to the head height of the driver. This method blocks the driver’s view significantly and was not a viable option, therefore an alternative mounting position was sought. The angled position as shown in Figure 5-13 is used, as in this position the IR imager can see the forward movements as well as the sideways movements.
Figure 5-13 Previous and new mounting position of IR Imager

Figure 5-14 shows the new changed algorithm before the use of the neural network. The initial pre processing part is the same as that of the previous algorithm. In processing the segmentation is based on a histogram. The further image processes like infrared image splitting and features extraction is different as the information will be used in a neural network.
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Infrared reading infrared thermograph

Infrared Interpolation

Pre Processing

Infrared Image

IR Imager
Angled Position

Processing

Segmentation based on histogram

Division of infrared image into three regions

Features extracted from region 1

Features extracted from region 2

Features extracted from region 3

Figure 5-14: advanced approach: Angled IR imaging algorithm
**Pre processing**

The pre processing algorithm is self explanatory from Figure 5-14. The detail is already covered in previous sections 5.1.2 and 5.2.1.

**Infrared Interpolation**

The infrared images taken from the experiment are interpolated from 16 pixel sq to 121 pixels square. As discussed earlier this interpolation on infrared image does not actually add anymore information into the system but the only advantage is to have a larger thermograph area to work on.

**Processing**

**Segmentation**

The devised adaptive segmentation method is based on the IR histogram (Figure 5-15). This method will compensate for slight temperature changes.

Now consider the histogram as a function called p(x). By taking the limits the maxima of the function p(x) can be given as:

\[
\begin{align*}
p(x), & \ 0 \leq x \leq 40 \\
\frac{df}{dx}(x) = p(x)
\end{align*}
\]  

(Equation 6)

Solving for the first derivative of p(x) function give two maxima values. The limit for the equation will then be the x value of f'(x) value. Then the minima intensity value within the limit of those maxima values is the threshold value for that particular image. This segmentation technique is calculated for each single infrared
image. Looking for two prominent peaks and taking the minimum value within those maxima ranges as depicted in Figure 5-15.

![Graph showing maxima and minima](image)

**Figure 5-15: Determination of segmentation value**

**Infrared Image splitting**

After interpolation and segmentation, the infrared thermograph is divided into three regions.

The infrared imager is 1 metre away at an angle of 60 degrees to the front left pillar of the car, see section 7.3. The field of view is 355 millimetre square. Each division of the thermograph image is based on mainly the three different region of the occupant (refer Figure 5-16). These are
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- R1 region is the background mostly with rare occurrences of head, shoulders and hands while driving. The region cover the R1 is 178 millimetres by 205 millimetres into 61 pixels by 80 pixels.

- R2 region is the face or head region. This region will allow focusing only on head movement and its temperature. The head region also covers 178 millimetres by 205 millimetres into 61 pixels by 80 pixels.

- R3 region covers shoulder, arm and hand movements. This region is the region with most movements whenever driver changes posture or moves slightly. This section is the lower section of the infrared image which is converted from 152 millimetres by 355 millimetres field of view to 121 pixels by 41 pixels.

![Interpolated Thermograph](image)

**Figure 5-16 Region allocation of infrared image**

**Image feature selection**

Selection of features from the image is the most vital step for the imaging algorithm to give useful and accurate results. Therefore a great deal of care is to be taken while
selecting them. A procedure is devised to find the appropriate feature for neural network input (see Figure 5-17).

![Feature selection process diagram]

The driver performs the majority of his movements by the upper half of the body. Therefore the infrared imager is also focused to monitor the upper body half movements. In future additional information on lower body (feet) can easily be obtained from pedal sensors like brake, throttle and clutch. Those movements are head turning, arm movements, torso movements and different combinations of them.
As the infrared image is divided into three different regions each region is dealt with separately as far as features selection and recognition is concerned.

1. ‘Head region’ is focused on head turning movement; this region will find where the driver is looking (refer Figure 5-18). The three movements for which the network will be trained are looking left, looking right and looking ahead (i.e. on road).

Figure 5-18: ‘Head region’ shown in interpolated infrared image
2. 'Torso region' is indirectly linked to torso movement as it will monitor head and neck movement in back and forth action (refer Figure 5-19). The three postures that will be defined in the neural network are no-leaning posture, leaning posture and looking down posture.

Figure 5-19: ‘Torso region’ shown in interpolated infrared image
3. ‘Shoulder and arm region’ shows two postures that will be trained for the neural network. There are hands-on steering and hands-off steering wheel (refer Figure 5-20).

Figure 5-20: ‘Shoulder and arm region’ shown in interpolated infrared image

A total of 18 different driver postures have been identified from these three regions. Neural networks will be trained to uniquely identify these postures from thermal images.

The shoulder and arm region can show if the car is stationary or in a moving state based on the assumption that driver’s hands will be on the steering wheel when he is driving the vehicle and vice versa. Bigger angle germanium lens can be used to get a larger FOV to get lower part of steering wheel in focus. The other two infrared image regions can identify the position of the driver. Detailed discussion of what can be achieved can be found in the results and discussion chapter 9.
Table 5-1 gives the idea of what region is for what type of posture movement detection.

<table>
<thead>
<tr>
<th>Infrared cropped region</th>
<th>Posture movement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Head region</td>
<td>Turning head</td>
</tr>
<tr>
<td></td>
<td>(Left, right and ahead)</td>
</tr>
<tr>
<td>Torso region</td>
<td>Back and forth movement</td>
</tr>
<tr>
<td></td>
<td>(Straight torso, Leaning and Looking down)</td>
</tr>
<tr>
<td>Shoulder and arm region</td>
<td>Hand on-steering and hands off-steering</td>
</tr>
</tbody>
</table>

Table 5-1: Posture and cropped region

**P-code description**

For neural network results to be easily readable a numerical value for each region is allocated which points to a particular type of posture. These numerical values are then stored in a look-up table. This look-up table is then used to make up a letter code which indicates what the driver is doing (see Table 5-2).
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<table>
<thead>
<tr>
<th>Region</th>
<th>ANN Numerical output</th>
<th>Posture description</th>
<th>P-code</th>
</tr>
</thead>
<tbody>
<tr>
<td>R1</td>
<td>1</td>
<td>upright posture</td>
<td>N</td>
</tr>
<tr>
<td>R1</td>
<td>2</td>
<td>Leaning</td>
<td>E</td>
</tr>
<tr>
<td>R1</td>
<td>3</td>
<td>Looking Down</td>
<td>D</td>
</tr>
<tr>
<td>R2</td>
<td>1</td>
<td>Looking Ahead</td>
<td>F</td>
</tr>
<tr>
<td>R2</td>
<td>2</td>
<td>Looking Left</td>
<td>L</td>
</tr>
<tr>
<td>R2</td>
<td>3</td>
<td>Looking Right</td>
<td>R</td>
</tr>
<tr>
<td>R3</td>
<td>1</td>
<td>Hands on Steering</td>
<td>S</td>
</tr>
<tr>
<td>R3</td>
<td>2</td>
<td>Hands not on Steering</td>
<td>NS</td>
</tr>
</tbody>
</table>

Table 5-2: Posture Code

So all three region codes are combined to describe a certain posture for example N-R-S means upright, looking right with hands on the steering wheel, which is a posture, for example, if someone is at a roundabout (see later the comparison with real video data).

Again D-L-NS means looking down on the left side with hands not on the steering wheel, which means that the driver might be putting the seat belt on or doing something other than driving.
5.3. Summary

- Differences in visual and IR thermographs are compared. Visual images consist of light intensity values whereas IR thermographs consist of actual temperatures.

- Phase 1: Initial imaging algorithm consists of two sections, pre-processing and processing. Pre-processing includes reading of IR thermographs and their interpolation.

- Phase 1 processing includes three processes; segmentation, feature extraction and tracking. The segmentation conducted is based on the temperature range. After segmentation, imaging features (centroid, centre X and centre Y) are extracted which are plotted as a graph. This graph is then used for tracking movement of the driver.

- Phase 2: Advanced approach – Angled IR algorithm includes two sections, pre-processing which is similar to that of the Phase 1 algorithm.

- Phase 2 processing section, which includes segmentation based on a thermograph histogram. Later the IR thermograph is split into three image sections. For each image section image features are extracted. The selection of features are based on the type of neural network and discussed in the next chapter.
6. **Artificial Neural Network**

Artificial intelligence (AI) is defined as synthetic intelligence by a system which is generally assumed to be a computer. Artificial intelligence is a well researched area in the field of computing. There are two branches of AI, Conventional AI and Computational Intelligence (CI).

CI processes include development, learning or training. The most well-known computational intelligence processes are:

- Fuzzy logic
- Artificial neural networks (ANN)
- Evolutionary or genetic computation
- Hybrid intelligence networks

### 6.1. Comparison of fuzzy logic and artificial neural network

Strengths and weaknesses of fuzzy logic and artificial neural networks are compared to decide which type of CI is ideal for imaging processes used in this thesis. Fuzzy logic is usually used for reasoning with condition of uncertainty. A Fuzzy logic output decision is based on a continuum of possibilities and embodies the alternative "maybe" to determine the probability of inclusion in a certain membership class
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whereas neural networks are used for complex decision making. Fuzzy logic decision curves are mostly linear which is not ideal for differentiating feature recognition. Pattern recognition is the main strength of ANN. For image processing there are specialised learning networks that perform better than other neural network types. Certain ANN can take data without training and classify them appropriately, such as self organized map.

For some control systems and applications fuzzy logic is preferred and for others an artificial neural network is used. Artificial neural networks are preferred for imaging applications and pattern recognition (Dubey et al., 2006) and are used in this thesis.

6.2. Types of neural network under consideration

Complex tasks are performed by neural networks, for example forecasting earnings, stock trading, fraud detection, hand writing recognition, speech recognition and other complex decisions. There are several types of neural networks but in this thesis only three types of networks are compared with each other for ideal results. These neural networks are the most widely used and are as follows:

1. Back propagation neural network or Feed forward neural network (BPN)

2. Radial based neural network (RBN)

3. Self organized map (SOM)

Each neural network is designed for different purposes. These selected neural networks are the most common types that are used and known for their pattern recognition capabilities (Al-Habaibeh et al., 2003, Haykin, 1999).

A scatter-gram is a graph used in statistics to visually display and relate two or more quantitative variables. In image feature processing using scatter-grams to visually
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relate features is a widespread method that is done before using any kind of decision making method. Infrared thermograph features are extracted and plotted using scatter-grams, which allow the selection of features as the inputs of neural networks, visually before creating the neural network.

6.2.1. Scatter-gram selection method for neural network input vectors

Infrared images were taken of two subjects (male and female). Several segmented infrared images from each subject's experiment database were selected applied to eighteen different postures that are required by the neural network to be trained. Each image is cropped into three regions as described in section 5.2.2. For each posture a minimum of ten region infrared images and maximum of thirty region infrared images were taken depending upon the frequency and importance of the driving task.

These blocks of infrared images are then analysed using the image processing software MATLAB to find the features. The features that are extracted from the region block are as follows:

- **Area**
  Find the binary image area in pixel squares.

- **Aspect ratio**
  Give the aspect ratio of the image. The aspect ratio of an image is its displayed width (horizontal) divided by its displayed height (vertical).

- **Object’s area and bounding box ratio**
  This features is the ratio of 'area of the object' and 'area of the bounding box'

- **Box width and height ratio**
  Box X/Y is the ratio of the bounding box width (X) and height (Y).
- Centre-X
  This feature takes the x-coordinate of the centroid of the object.

- Centre-Y
  This feature takes the y-coordinate of the centroid of the object.

- Density (mean)
  Reports mean intensity or density of the object.

- Angle
  This feature reports the angle between the vertical axis and the major axis of the ellipse equivalent.

- Holes
  Finds and reports the number of holes.

- Hole Area
  This feature reports the area of the hole within an object.

- Hole Ratio
  Hole ratio is determined by Area / (Area + Hole).

- Major and minor axis
  Reports the length of the major axis and minor axis of the ellipse equivalent.

- Diameter (mean, max and min)
  This feature gives the minimum, maximum or mean of the outline points and passing through the centroid of that object.
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- **Radius (max and min)**
  Finds and report the minimum and maximum distance from the centroid to the object perimeter.

- **Perimeter**
  Gives the outline length of the object, this includes the holes outline length.

- **Radius Ratio**
  Radius ratio is calculated by minimum radius divided by maximum radius.

- **Roundness**
  Roundness is calculated by using the formula
  \[ \frac{\text{Perimeter}}{2 \times \pi \times \text{Area}} \]

- **Box width and box height**
  This gives the object bounding box width and box height.

The scatter-grams (as shown in Figure 6-1) are plotted for features that are listed above. The values from the thermograph features are plotted to show different groups visually. For example the Figure 6-1 shows area feature plotted against number of samples and shows grouping of different driver postures for that particular region. Only a few of the above features showed distinguishable results that can be used for pattern recognition in a neural network.
The overlapped features in scatter-grams represent when trained in the neural network will result in inaccurate result (see Figure 6-2). It can be said with confidence that a neural network trained with data from Figure 6-1 will yield better accuracy than the neural network trained with Figure 6-2. This will be true for all kinds of networks as there is no way of distinguishing between the mixed or overlapped data.
Figure 6-2: Area/Bounding box scatter-gram of head region

The features used as an input in the neural networks are shown in the following Table 6-1 (see Figure 5-16):

<table>
<thead>
<tr>
<th>Infrared cropped region</th>
<th>Selected features</th>
</tr>
</thead>
<tbody>
<tr>
<td>Head region</td>
<td>Angle (Figure 6-3) and Segmented Area</td>
</tr>
<tr>
<td></td>
<td>(Figure 6-4)</td>
</tr>
<tr>
<td>Torso region</td>
<td>Area (Figure 6-5)</td>
</tr>
<tr>
<td>Shoulder and arm region</td>
<td>Area (Figure 6-6)</td>
</tr>
</tbody>
</table>

Table 6-1: Selected features for neural network
Figure 6-3: Head region angle scatter-gram

Figure 6-4: Head region area scatter-gram
Slight overlapping of scatter gram data as in Figure 6-4 i.e. looking left and looking ahead is not a major issue because the safety system’s infrared imager frequency is 4 FPS and therefore the system is analysing 4 thermographs every second. If one thermograph of looking left is in the looking ahead region the subsequent three may be in the looking left region.

Figure 6-3 to Figure 6-6 show the scatter-gram for actual training set generated for the subject. The data is ready for training in a neural network.
6.3. Neural network designs

Designing a neural network require several parameters to be considered. The types of inputs required, how many input vectors, number of neurons in a hidden layer if it is a Feed-Forward Back Propagation Neural Network (FFB), number of hidden layers if it is a FFB network, number of outputs, how the outputs will represent the results. There is no certain formula for setting up these parameters but neural network design optimization is more of an iterative process.

Before starting the design of a neural network the output of the network should be defined. There are eighteen different positions that needed to be defined by this neural network. The output can be a single output if a single neural network with linear function is used. It can also be multiple outputs but then it needed to show how these eighteen different postures are defined in a multiple output neural network.
6.4. **Single neural network designs**

6.4.1. **Large input single FFB neural network design**

A single binary array was used as a neural network input for the initial neural network design. This binary array was equal to the number of pixels in the raw infrared image which is 256. The segmented infrared image is used as an input for the network. For number of inputs equal to 256 the hidden layer needs to be carefully laid out. It could be a single hidden layer or several hidden layers. There will be at least 350 neurons in the network, which is a large network to work with. The training time would be significantly large for multi layered and self-organized networks and the network would take significant memory. This type of network design is not preferred see Figure 6-7.

![Figure 6-7: Segmented image input into multi layered neural network](image-url)
6.4.2. Feature based single FFB neural network design

The other method is to identify features from the infrared image and use them as an input for the neural networks. This network design will consume less memory and CPU power. It will be faster in training and simulation than the previous network design which is much larger. The features need to be carefully selected, for a six (6) feature neural network design there will be approximately 15 neurons in a network (see Figure 6-8).

![Figure 6-8: Features based input into multi layered neural network](image-url)
The output needs to be linear as there are eighteen different outputs required by a single network. The network requires extensive and large training sets to be trained on. Eighteen different outputs from a single output neuron is to achieve with average accuracy.

6.4.3. Feature based Radial Neural network design

The advantages of Radial based function (RBF) neural network design is that they are constructed in a fraction of the time that it takes linear based neural networks like FFB to train. The training of a Radial based network (RBN) is done when it is constructed. On the other hand a RBN takes a lot of memory due to the number of neurons. The input of the RBN is the same as that of a feature based FBN network (see Figure 6-9). Features are extracted from the IR imagery. The output neuron is setup as a linear function to identify eighteen different driving postures.

![Feature based radial network design](image_url)
6.4.4. Self organized map network design

Self organised map network is unsupervised learned design. For detecting eighteen different driver postures self-organized map type network gives various results thus this type of design is ruled out.

6.5. Three Neural Network design: TNN

This novel neural network design is based on a principle of combining small neural networks together. This design consists of three neural networks; each neural network is related to region features as shown in Figure 6-10 (see section 5.2.2 for explanation on image regions and section 6.2.1 for region features). The results from all three neural networks are combined together to form a posture code (p-code) (see section 5.2.2 for p-code details).
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Figure 6-10: Novel neural network design: TNN
6.5.1. Three neural network design evaluation

Neural networks for each of the three regions as shown in Figure 6-10 are separate. This means that there will be three neural networks working simultaneously on a single thermograph. Furthermore, for each region, three different types of neural networks are constructed. They are FFB, RBN, and SOM networks. Comparison and evaluation of all three networks results in finding the best neural network for a particular region. These types are selected because they have good ability to differentiate between different parameters. The construction parameters of all nine neural networks are listed in Table 6-2).

<table>
<thead>
<tr>
<th>Region 1 ‘R1’</th>
<th>Region 2 ‘R2’</th>
<th>Region 3 ‘R3’</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inputs</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 (area R1)</td>
<td>2 (area/angle R2 &amp; area R2)</td>
<td>1 (area R3)</td>
</tr>
<tr>
<td>Target outputs</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 neuron,</td>
<td>1 neuron,</td>
<td>1 neuron,</td>
</tr>
<tr>
<td>3 output values</td>
<td>3 output values</td>
<td>2 output values</td>
</tr>
<tr>
<td>FFB</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Layers 2</td>
<td>Layers 2</td>
<td>Layers 2</td>
</tr>
<tr>
<td>Neurons 2</td>
<td>Neurons 5</td>
<td>Neurons 2</td>
</tr>
<tr>
<td>Inner Layer: Sigmoid function</td>
<td>Inner Layer: Sigmoid function</td>
<td>Inner Layer: Sigmoid function</td>
</tr>
<tr>
<td>Output Layer: Linear function</td>
<td>Output Layer: Linear function</td>
<td>Output Layer: Linear function</td>
</tr>
<tr>
<td>Goal: 0.001</td>
<td>Goal: 0.001</td>
<td>Goal: 0.001</td>
</tr>
<tr>
<td>RBN</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spread constant: 1</td>
<td>Spread constant: 1</td>
<td>Spread constant: 1</td>
</tr>
<tr>
<td>Inner Layer: Radial function</td>
<td>Inner Layer: Radial function</td>
<td>Inner Layer: Radial function</td>
</tr>
<tr>
<td>Output Layer: Linear function</td>
<td>Output Layer: Linear function</td>
<td>Output Layer: Linear function</td>
</tr>
<tr>
<td>SOM</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Goal: 0</td>
<td>Goal: 0</td>
<td>Goal: 0</td>
</tr>
<tr>
<td>Epochs: 25</td>
<td>Epochs: 25</td>
<td>Epochs: 25</td>
</tr>
</tbody>
</table>

Table 6-2 Neural network specifications
Thus training data is selected to cover all types of motions and the frequency of motion. The training data for each volunteer driver is three hundred (300) samples for each region neural network. The simulation data is three times the size of the training set which is nine hundred (900) samples for each subject.

6.5.2. Selection and training of the three neural network design

The actual ANN results are plotted in section 8.2. The different postures are linked with a numerical postural code. Each numerical value represents a particular posture. The closer the actual result plot is to the posture code the more accurate is the detection.

Only one type of ANN is required for each region. For selection of the most appropriate ANN from FFB, RBN and SOM two volunteer drivers were randomly selected.

The SOM network gives a range of values. By making the decision lines on the output graph of the SOM, a posture code can be found.

The RBN network is moderately accurate but gives unexpected results sometimes. Also it can be seen from the results (Figure 6-11 and Figure 6-12) that looking ahead is one of the principle tasks that a driver performs. The error is found in the looking right posture. This error affects the final decision of the posture detection algorithm as there are 3 different regions, which are combined together to get the final result. The posture detection algorithm will be running at 4 FPS, i.e. analysing four (4) thermographs each second. If one thermograph ANN output result shows abnormality or inaccuracy the remaining three (3) thermographs may be able to remove the abnormality or inaccuracy.
The graphs shown in Figure 6-11, Figure 6-12 and Figure 6-13 are the results of compared neural networks. Each posture code section in the graphs shows three neural networks. These neural network results can be Zero (0), One (1) or Two (2) with the exception of the SOM neural network as these networks are self trained and thus their outputs are uncontrolled. If the result is as expected, i.e. ideal, the resulting plot will be Zero (0). The results can deviate from Zero (0) up to Two (2), this shows the error. This does not mean that the neural network is inaccurate based on a single plot. If a certain neural network deviates from the Zero (0) line this means that particular network is not suitable for the feature recognition task. It is generally seen that FFB neural networks are most suitable for feature recognition tasks as they have previously been trained using supervised learning and contain a linear transfer function.
The radial basis network gives unreliable results. The self organized map is reliable except for some data it was unable to process and distinguish and starts hence to give random values. Therefore a neural network based on this FFB network is strongly recommended in the second region case.

The FFB network gives a consistent performance with error percentage not significantly high.
The SOM performed well in the first subject third region but this was not the case with the second subject (see Figure 6-13). As both cases varied in amount of skin covered and movement behaviour thus making human posture behaviours unpredictable, thus the FFB network is the preferred choice for the third region.
The 'Arm and shoulder' region is easier because only two outputs are required from a single stream of input data. Thus all networks performed significantly well, with the SOM and FBN network achieving an accuracy of 100% on all samples. Thus making FBN network preferred choice being training based neural network.

The neural network for each subject will be trained individually. Therefore the system can detect the same posture with similar accuracy for all subjects. This means that a person with long hair or short hair will not have errors in the safety system depending upon their different features. Even though FFB and SOM networks both
gave accurate results the preferred choice of network in this case is also FFB. The FFB network is more stable as it was trained on sample data previously. SOM also gave out random results with unexpected data this kind of behaviour is not expected from FFB networks.

6.6. Summary

- Using related literature artificial intelligence techniques like fuzzy logic are compared with the artificial neural network (ANN). ANN is preferred as these networks are a more flexible choice than fuzzy logic. An ANN can be trained over and over again.

- Three types of neural network are considered and compared. These networks are FFB, RBN and SOM.

- Initially the neural network designs are single network based. Several neural networks designs are shown.

- The first design shows the input of a large array of pixels in an FFB neural network with a single output. The second design shows a single FFB neural network with infrared thermograph features as an input. The other designs were similar and based on RBN and SOM networks.

- Finally a novel design of three FFB network design working on split infrared thermographs is described.

- Training of the Novel ANN design is described. Also compared are FFB, RBN and SOM for the novel ANN designed. FFB was the preferred choice for all three neural networks.
7. Experimental Setup

7.1. Introduction

This chapter evaluates the safety system, which was designed and developed in previous two chapters by experimentation. It gives a detailed account of how the experimentation was conducted.

7.2. Experiment 1: Trials with Infrared camera pointed from the windscreen

7.2.1. Aim of the experiment

This was the first experiment conducted for this research. The aim of this initial experiment was to find the capabilities and limitations of the low resolution IR imager in a driving environment, i.e. how well a low resolution IRISYS imager can track a driver’s movements. Another result that is required from the experiment is to find the accuracy of the infrared imager in terms of measuring driver movements.

A secondary aim of the experiment conducted was to see whether the IRISYS thermal imager could be used as a vehicle occupant identification sensor. For more details on this see Appendix C.
7.2.2. Driving simulator

The driving simulator was installed in an ergonomics test facility with a STISIM driving simulator which is discussed in Section 3.7. The driving simulator was built on a static Ford Scorpio with front projection of 3 metres by 2.5 metres shown in Figure 7-1. The control room consists of a driver communication system and the STISIM control computer. The driver is kept in contact via the driver communication system during the length of the experiment. The data acquisition system was standalone and will be discussed in detail in Section 7.2.4.

Figure 7-1 (A) Shows car simulator running scenario and Infrared camera, (B) Simulation Control
The STISIM system

An overview of the STISIM platform is discussed in section 3.7. In this section interfacing and programming of scenarios is discussed briefly.

The main controller for the STISIM driving simulator is an IBM PC.

The STISIM simulator hardware requirements are as follows:

- IBM PC which is 80486 equivalent or better
- At least 4MB RAM
- Hard Disk Drive
- Parallel Port
- 34020 based TIGA graphics board capable of 1024x786 resolution
- VGA graphics card
- Digital I/O and A/D interface card, CIO-DAS08/JR series from Measurement computing Inc used.
- Sound card
- STISIM Hardware protection key

Figure 7-2 shows the interfacing of sensors with the STISIM driving simulator controller.
The STISIM driving simulator is programmed using the MS-DOS operating system. The simulator is designed such that it provides the driver with a very realistic driving experience, using visual display and audio sounds as feedback to driver actions. For example crashing a car shows visual as well as audio display to the driver for the crash scenario.

Three input files are used to vary the scenario elements during the simulation run. All these files are in ASCII format and can be changed in text editor. These files are as follows:
• **STISIM.COL**
  This file defines the colour displays. The colours defined are for the objects that are displayed on the roadway scene in the simulation.

• **GAINS FILE**
  This file is the primary configuration file of STISIM simulator. Parameters in this file influence the vehicle dynamics, visual display, transport delay, vehicle handling characteristics.

Vehicle dynamics can be divided into steering, speed control and transmission. Figure 7-3 shows the steering control of the simulator.

![Steering control for STISIM simulator](image)

Figure 7-3: Steering control for STISIM simulator

Figure 7-4 shows the speed control and parameters that influence the speed.
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Figure 7-4: Speed control for STISIM simulator

Figure 7-5 shows the speed control with transmission and engine revolution consideration.

Figure 7-5: Speed control with transmission consideration for STISIM Simulator

• EVENTS FILE
This file, as the name suggests, will describe all the events that will occur during the simulation run. The events in the file are user definable and there are several performance measures that can be selected. It is possible to activate several events at the same time, for example creating an intersection, crossing of pedestrians, oncoming vehicles and cross traffic. This can be done by using SDL (Scenario define language) command language. The SDL command language contains two parts, the first part defines the events and the second part collects data for which performance measures are selected. It also uses pre-defined events and sub-routines to simplify the programming procedure.
The events part of the file follows the general format as:

ON DISTANCE, EVENT SPECIFIER, PARAMETER 1, ..., PARAMETER N, COMMENTS

The following ‘event specifiers’ are the most commonly used during the programming of the event file:

- A: Vehicle ahead of subject, from other lane
- BLCK: Display blocks on the display screen
- BSAV: Starts saving dynamics data
- ESAV: Ends saving dynamics data
- C: Add curvature to the roadway
- CT: Cross traffic at intersection
- CV: Control vehicle automatically
- DL: Double lane change
- DI: Digital input event
- DO: Digital output event
- ES: End simulation
- I: Display intersection
- IA: Display intersection sign
- LS: Speed limit change
- PDE: Previously defined event
- PED: Pedestrian display
- ROAD: Displays a specific roadway
- SA: Displays traffic signal sign
- SL: Traffic signal light

The second part of the event file can record performance parameters. Performance measures used and recorded in the experimental runs are as follows:
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- Time
- Speed
- Vehicle curvature
- Road curvature
- Distance travelled
- Steering wheel angle
- Throttle acceleration - deceleration
- Braking acceleration – deceleration

**Scenario**

The scenario selected for the experiment was urban busy traffic which lasted for 20 minutes approximately. An urban traffic scene was selected because the number of tasks during driving is much higher than that of motorway driving. The scenario was created with traffic signals and five (5) intersections at random intervals, see Figure 7-6. The pedestrian crossing is also taken into consideration to simulate real driving behaviour. Before the experiment the volunteers were instructed about the various driving tasks, such as intersections, overtaking, lane changes, pedestrian crossings, looking left or right before making a turn or arriving at the cross road and waiting for a signal, lane changing manoeuvres, looking at side and rear view mirrors. This was to ensure that the experiment conducted would be as realistic as possible. For example as shown in Figure 7-6 the volunteer drives up to the red traffic signal. The diver has to consider pedestrians crossing; looking left and right after the traffic signal turns green. Further tasks conducted during the scenario run include putting on
the seat belt, adjusting mirrors, looking in the rear view mirror, looking left or right, using a swipe card to simulate entrance or exit of secured car park, mobile phone usage while driving and using an in-car stereo system or climate control.

Figure 7-6 Bird's eye view of the intersection scenario

The simulation room was kept in darkness to simulate night time and the working of IR imager in night time. The IR imager exhibited no major change in light or dark surroundings.
7.2.3. Reference sensors

The experiment included two reference sensors.

1. Visual camera

2. Talley pressure Matrix

The primary sensor for the safety system is the IRISYS Imager. A visual camera and the Talley pressure monitor acted as the reference aids during the experiment. The webcam and pressure monitor were mounted to find the position of the human subject and to check the approximate distance of the movements detected by the thermal imager. The IRISYS thermal imager and webcam were mounted together, looking from 1 metre away from the subject from the front. As this was an initial experiment the position of the infrared camera and webcam did not make a major difference, as the aim was to find the capabilities of the infrared imager.

The pressure mat was placed on the sitting area of the subject for which the pressure is measured for each air pocket (see section 3.5).

Visual Camera

The visual camera used for the experiment was an entry level CMOS webcam by Logitech® (see Figure 7-7). The idea was to acquire the visual image and IR thermograph simultaneously. The camera was mounted directly above the IRISYS Imager therefore sharing the same FOV.
Talley Pressure Matrix

The Talley pressure matrix was used to help find the position of the driver with reference to the driving seat. This can also help find the driver's weight and can tell if the driver is leaning. This pressure monitor is connected to the RS-232C port of the data acquisition system.

Two data sets from the Talley pressure monitor were taken, the first set at the beginning of the experiment and another at the end of the experiment. The Talley pressure monitor takes data by inflating and deflating the air pockets (see section 3.5); this process takes up to a minute, which is relatively slow for real-time processing. This counted as a disadvantage of this sensor and it was excluded from the later experimental stages because of this slow response timing of the sensor. Other means like visual camera and manual height and weight readings were taken in later experiments.
7.2.4. Data Acquisition platform

The Data acquisition system was designed based on the experiments that were to conducted in this research programme. It involves consideration of hardware interfacing of devices with the acquisition system, software for organizing and collection of data on disk drives and understanding of IR imager and visual camera protocols. Figure 7-8 shows the data acquisition platform schematic.

![Figure 7-8: Data acquisition schematic](image)

The following sections will explore each section in more detail.
The software supplied by the IRISYS IRI1002 thermal imager only measures and records certain pixels at one time. Therefore online thermal imaging software which is supplied by IRISYS is very limited, see Figure 7-9. To display and record the complete thermograph the author had to develop his own software.
Significant modifications were done to the existing software to fulfill the requirements of the experiments (see Figure 7-11).
The following is the list of major modifications that were made:

- Unlimited acquisition of both infrared and visual data. No time limit.

- Time interval is decreased, the software can now acquire up to 4 FPS.

- Previously the software was unstable. Significant changes to the hardware interfacing code were done to make the software more stable and usable on different operating systems. Compatible operating systems included Microsoft Windows 2000 and XP.

- File naming and storing was restructured making data acquisition more organisable. This is required as vast amounts of data would be stored during the experiment runs. Therefore batch renaming and storing data in folders is included.
• Simple file naming and directory structure can be performed from software interface.

The software gives detail status of what task is being performed.

**IRISYS Imager: Serial Protocol programming**

The IRISYS IRI1002 thermal imager has its own protocol which needed to be converted into an infrared image. The software has to be compatible with hardware specifications for the thermal imager *i.e.* 1,15,200 baud, 8 data bits, no parity, 1 stop bit, no handshaking. (See Appendix D)

The IRISYS IRI1002 sends thermal data only when a certain command is written to it through a serial port. Further details and its construction are discussed in the section 3.2.2.

**Visual Camera acquisition technology**

Microsoft® DirectShow® is an architecture for streaming media on the Microsoft Windows® platform. It supports capture using Windows Driver Model (WDM) devices or older Video for Windows devices. DirectShow® is integrated with other Microsoft DirectX® technologies. It detects and uses video and audio acceleration hardware when available, but also supports systems without acceleration hardware, therefore can be used with vast variety of compatible IBM-PC running Microsoft operating system.

Technology used in the software is WDM ActiveX™ which is from MarvelSoft® called VideoOCX. This control is backward compatible with most Video-for-Windows (VFW) devices, such as USB cameras (webcams) and framegrabbers in conjunction with a CCD camera or camcorder. VideoOCX works smoothly in most
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ActiveX™ hosting environments, such as Lab/Windows and Visual Basic. Applications range from professional scientific image processing and surveillance to computer vision and general multimedia programs. This control is independent of the interface, frame rate of the device or the Microsoft® OS used.

Thus this control gives us the flexibility of making software more flexible as it can capture data in real-time. This control also gives some image processing capabilities that are not built into the visual device.

**Interfacing sensors**

Three sensors were required to be interfaced with the data acquisition PC see Figure 7-12. These sensors are:

- IRISYS Thermal Imager: Interfaced using DB-9 connector to a Serial COM1 port.

- Talley pressure monitor: Interfaced using DB-9 connector to a Serial COM2 port.

- Logitech Messenger webcam: Interfaced using USB 1.1
Figure 7-12: Interfacing of sensors with IBM-PC for Initial experiment
7.2.5. Mounting of IRISYS Imager

The IRISYS thermal imager was mounted in the test rig by using a custom made clamping stand (Figure 7-13).

Figure 7-13: During experiment, front mounting position of IRISYS thermal imager

This included placing a custom build clamp and placing it together with the back face plate of IRISYS thermal imager and a G-Clamp stand on which the IRISYS thermal imager mounts. The height of the G-Clamp stand is adjustable and it can be clamped using to an attached at the bottom end see Figure 7-14.
The IRISYS thermal imager and Logitech webcam are also joined together with each such that they have the same FOV see Figure 7-15.
The position and angle of the IRISYS thermal imager is measured by measuring tape and angle measurement tool respectively. In some special cases a tripod stand is also used for mounting the IRISYS imager. A level is required to make sure the IRISYS imager is in horizontal position see Figure 7-16.
7.2.6. Volunteer drivers for experiment

Eleven (11) volunteer drivers (see Figure 7-17) are selected for the experiment from sixteen (16) year old to sixty (60) year old. The selection was based on the volunteer driver experience, age, hair length and considering other facial features for example large forehead, beard and glasses. Figure 7-17 shows the visual reference image of the volunteer driver below which is the interpolated infrared thermograph. All data displayed is from the experimental data collected using the data acquisition system.
7.2.7. Offline data collected for Phase 1 Imaging Algorithm

The offline data that was collected from the STISIM simulator run lasts for 25 minutes on average per driver. The experimental data is stored on the hard disk drive on the data acquisition system which was later transferred to an offline platform where MatLAB is used for Phase 1 imaging algorithm processing. For more details on phase 1 imaging algorithm see Section 5.2.1
7.2.8. Experimental environment and temperature

During the thermograph acquisition the infrared imager was configured to remain accurate to 0.1 degrees. This can be obtained by a change in the parameters of the infrared camera. The experiment was conducted on different days at different times of the day to include the effect of day and night temperature in the experimentation. If the infrared camera is focused from the front i.e. the view used previously by Amin et al., (2004) the minimum temperature goes down up to 22-23 degrees, this is due to the background temperature of the car which is significantly lower due to steel construction of the car.

As the infrared imager detects heat emitting from the body, therefore, a limitation of the infrared imager is the presence of glass. Visual cameras can see through glass, but infrared imagers cannot. Therefore the infrared imager has to be installed inside the car so it can look directly at the driver. In this experiment the position of the infrared imager mounting was from the front looking directly at the driver. This position was later discarded due to the impracticality of mounting in the real car. The ideal position of mounting the infrared imager should provide a field of view 300 to 350 square millimetres as this field of view includes the head, shoulders and upper part of arms in most cases; this is what is intended to be used for this experiment. The right pillar (for right hand drive) is not considered as the field of view is too small as it uses a lens of 20 degrees. The other two locations under consideration were the rear view mirror position and left pillar. The rear view mirror position was considered but would create a protrusion and safety hazard for the driver and also the IRISYS thermal imager would need to be fitted with a wider angle lens. Thus the left pillar position for mounting the infrared imager was selected, as it was an ideal distance looking from 1 metre away giving a field of view of 14 inch sq at an angle of 60 degrees measuring from perpendicular to the head restrain of the car seat.

The maximum temperature from thermographs acquired from the infrared imager taken from 11 volunteers ranged from 37 to 39 degrees. This range is required to find the background separation which will help binary threshold the thermographs which
is explained in detail in section 5.2.1. Small temperature variations in the surroundings is also taken into consideration. Thus experiments were conducted at different times of day and on different days over a long period of time. The large temperature variations throughout the year are not considered.

7.2.9. Conclusion of experiment 1

Experiment 1 shows the capability of the IRISYS thermal imager. Even though the IRISYS thermal imager is not high resolution it can still track the movement of drivers after application of the imaging algorithm on the experimental data. The experiment 1 and phase 1 imaging algorithm can track movements but more detailed driver movement detection can be achieved by changing position of the IRISYS thermal imager and improving the imaging algorithm. Also the current mounting position of IRISYS thermal imager is not suitable in practice as it blocks drivers FOV and causes a safety hazard. Therefore experiment 2 was conducted as a more detailed and extensive trial based on a changed position of the IRISYS thermal imager and improved imaging algorithm.
7.3. Experiment 2: Experiment with infrared camera mounted on the passenger side screen pillar

7.3.1. Aim of the experiment

The IRISYS thermal imager was repositioned at an angle during this experiment (see Section 5.2.2). This allows the experiment to be more realistic than the previous experiment where the IRISYS mounting was blocking the driver’s FOV. Also the angled position of the thermal imager was expected to improve the previous tracking algorithm. The number of volunteer drivers who conducted the experiment is also increased.

7.3.2. Holywell STISIM Driving Simulator

The STISIM driving simulator was moved from its Factory Street location to a test rig in the university’s Holywell building. Figure 7-18 shows a view of the Holywell test rig while the experiment was being conducted.
The Holywell test rig (see Figure 7-19) allowed more flexibility in setting up the sensors and instrumentation. It also allows adjustment in accordance with the volunteer driver height and physique and instrument adjustment for each individual.

Setting up the Holywell test rig for STISIM driving simulator involved installing low cost sensors, setting up a projection screen and balancing the test rig.
Mounting low cost sensors

Potentiometer

The STISIM driving simulator uses potentiometers for the purpose of measuring rotation and linear motion. It eliminates the high cost of using an encoder.

The construction of a potentiometer is much simpler than that of an encoder (see Figure 7-20). 5 volts are applied to the potentiometer and voltage is measured as
shown in Figure 7-20A. This variable analogue signal is then digitised using a DAC board.

![Diagram of potentiometer and encoder](image)

Figure 7-20 Difference in construction of potentiometer and encoder

**Steering column mounting**

Mounting involved two timing pulley, one mounting onto the steering column shaft while the other was fixed to the potentiometer shaft, see Figure 7-21. The timing pulleys had a 1:1 ratio as both pulleys were identical (35mm diameter with 36 teeth). A rotational potentiometer was configured to give 4000 counts when digitized. The steering was then adjusted to give a reading of around 2000 counts and this point was selected as the centre position of steering (see Table 7-1). Complete steering wheel rotation movement was 400 degrees, 200 degrees on each side. Each 200 degrees gave 450 counts. Which is enough counts to make the simulation work and collect data. This construction gives an accuracy of 0.44 degrees per count.
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Figure 7-21 Shows potentiometer mounting on steering column (A) potentiometer, (B) timing belt

<table>
<thead>
<tr>
<th>Maximum left turn count</th>
<th>Centre Count of steering</th>
<th>Maximum right turn count</th>
</tr>
</thead>
<tbody>
<tr>
<td>1550</td>
<td>2000</td>
<td>2450</td>
</tr>
</tbody>
</table>

Table 7-1 Steering potentiometer absolute counts

For the throttle and brake the counts are shown in Table 7-2.

<table>
<thead>
<tr>
<th>Throttle Min – Max</th>
<th>0 – 3975 Counts</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brake Min – Max</td>
<td>0- 3975 counts</td>
</tr>
</tbody>
</table>

Table 7-2 Throttle and brake potentiometer absolute counts
Figure 7-22 shows the electrical diagram for interfacing the potentiometers with the STISIM DAC board.

Figure 7-22: Electrical diagrams of potentiometer connections
7.3.3. Angled mounting of the IRISYS Imager

The new mounting position of the IRISYS thermal imager was proposed in Section 5.2.2 and a modified version of the imaging algorithm was developed (see Figure 5-13).

Figure 7-23 shows the experimentation conducted with the new position of the IRISYS thermal imager.

![Figure 7-23: During the experiment: new position of IRISYS thermal imager](image)
7.3.4. 56 Channel LED controller

To study human response times ergonomists use light signals, usually Light Emitting Diodes (LEDs). This is a very useful technique that is used by ergonomists and others who require human response timing, for example rescue forces and air force pilots.

A 56 Channel LED custom built controller (see Figure 7-24) was used for getting responses from the driver during the experimentation by switching strategically placed LEDs.
This is required to get realistic posture movements from the driver. Five positions were carefully selected for setting up LEDs. The LED positions in the Holywell test rig were as follows:

- Left blind spot check
- Left side mirror position
- Rear view mirror position
Right side mirror position

Right blind spot check

During the first and second scenario experimental runs, the appropriate LEDs were turned on and off to elicit a particular driver response. This allowed the capturing of a driver's exact movements and posture by the thermal imager. For example take a left turn at a T-junction; before making the turn in real life the driver checks the rear view mirror, stops before the give-way line, looks both ways and then makes the left turn. In the experimental run for this manoeuvre the driver approaches the T-junction and before stopping the rear view mirror LED will light up, the driver response is to look at the LED; after stopping at the give-way line the driver looks at the right and left side-mirror position LEDs as they turn on and off twice and then the driver is allowed to make the turn.

This equipment was used for the first and second scenario runs only. The LED controller was controlled manually during these runs.

The third scenario run simulated motorway driving for monitoring fatigue and drowsiness in drivers. Therefore conditions in which there was no disturbance were critical to this test.
7.3.5. **Driving simulator scenarios**

Detailed driving simulator scenarios were programmed for this experiment and divided into three small experiments which were:

- Scenario 1: Driving task and Situational experimental run
- Scenario 2: Urban experimental run
- Scenario 3: Rural experimental run

*Scenario 1: Driving task and situational experimental run*

In this scenario the most common driving tasks were listed and programmed for five times in the STISIM simulator. The time for each driving task was noted. The driving tasks were as follows:

- T-Junction Right Turn
- Intersection Left Turn
- Crossing Roundabout
- Making U-Turn
- Emergency stop
- Putting seat belt on
• Reverse parking

LEDs were used to make driver use mirrors while they are driving.

Scenario 2: Urban experimental run

The Urban scenario was focused on city driving styles and was programmed with the following driving tasks and urban environment in mind:

• T-junction turns
• Intersection crossing
• Pedestrian crossings
• Merging onto a dual carriageway
• Traffic signals
• Speed limit
• Forced overtaking manoeuvre
• Fog
• Emergency stop by the car ahead

This scenario required the driver to be attentive all the time during the run. The LEDs were flashed during the run to make sure driver looked in all the mirrors. The aim was to make the urban driving behaviour close to reality.
**Scenario 3: Rural experimental run**

This scenario was programmed for monitoring fatigue and sleepiness in drivers while driving. Therefore a long curving road was programmed in a scenario which lasted for over 50 minutes. Curtains were drawn over the driving simulator test rig to give the driver a sense of driving alone. The noise was cut to a minimum and less traffic was shown on the road. The driver was asked to maintain a speed of 60 Mph.

### 7.3.6. Volunteer drivers

A total of twenty (20) volunteer drivers were selected for the experiment, with the selection based on gender and age. Half of both genders were over the age of 50. Table 7-3, Table 7-4, Table 7-5 and Table 7-6 shows the information about the subjects selected.
### Male Subjects

<table>
<thead>
<tr>
<th>ID</th>
<th>Age (yrs)</th>
<th>Ht (cm)</th>
<th>Wt. (kg)</th>
<th>Gender</th>
<th>Glasses</th>
<th>Hair style</th>
<th>Beard/ Shave</th>
<th>Moustache</th>
<th>Cap</th>
<th>Driving exp.</th>
</tr>
</thead>
<tbody>
<tr>
<td>M01</td>
<td>42</td>
<td>153</td>
<td>73</td>
<td>M</td>
<td>Yes</td>
<td>Short covered 2cm</td>
<td>Beard</td>
<td>No</td>
<td>Yes</td>
<td>20</td>
</tr>
<tr>
<td>M02</td>
<td>35</td>
<td>172</td>
<td>70</td>
<td>M</td>
<td>Yes</td>
<td>Big forehead- short hair 1cm</td>
<td>Beard</td>
<td>Yes</td>
<td>No</td>
<td>7</td>
</tr>
<tr>
<td>M03</td>
<td>25</td>
<td>175</td>
<td>55</td>
<td>M</td>
<td>No</td>
<td>Flat black 2cm</td>
<td>Shaved</td>
<td>No</td>
<td>No</td>
<td>1</td>
</tr>
<tr>
<td>M04</td>
<td>29</td>
<td>171</td>
<td>85</td>
<td>M</td>
<td>Yes</td>
<td>Stuck up from front 1cm</td>
<td>Shaved</td>
<td>No</td>
<td>No</td>
<td>10</td>
</tr>
<tr>
<td>M05</td>
<td>27</td>
<td>182</td>
<td>82</td>
<td>M</td>
<td>Yes</td>
<td>Short hair 1cm with p-cap</td>
<td>Shaved</td>
<td>No</td>
<td>Yes</td>
<td>8</td>
</tr>
</tbody>
</table>

**Table 7-3: Male volunteer drivers selected for experiment 2 (below 50)**

### Female Subjects

<table>
<thead>
<tr>
<th>ID</th>
<th>Age</th>
<th>Ht. (cm)</th>
<th>Wt. (kg)</th>
<th>Gender</th>
<th>Glasses</th>
<th>Hair style</th>
<th>Beard/ Shaved</th>
<th>Moustache</th>
<th>Cap</th>
<th>Driving exp.</th>
</tr>
</thead>
<tbody>
<tr>
<td>F01</td>
<td>27</td>
<td>159</td>
<td>57</td>
<td>F</td>
<td>no</td>
<td>Medium blond 25cm</td>
<td>N/A</td>
<td>N/A</td>
<td>No</td>
<td>7</td>
</tr>
<tr>
<td>F02</td>
<td>27</td>
<td>165</td>
<td>52</td>
<td>F</td>
<td>no</td>
<td>Long curly hair 50cm</td>
<td>N/A</td>
<td>N/A</td>
<td>No</td>
<td>3</td>
</tr>
<tr>
<td>F03</td>
<td>21</td>
<td>170</td>
<td>58</td>
<td>F</td>
<td>no</td>
<td>Long straight hair 40cm</td>
<td>N/A</td>
<td>N/A</td>
<td>No</td>
<td>3</td>
</tr>
<tr>
<td>F04</td>
<td>24</td>
<td>159</td>
<td>58</td>
<td>F</td>
<td>no</td>
<td>Pigtail (tied hair) 30cm</td>
<td>N/A</td>
<td>N/A</td>
<td>No</td>
<td>3 Months</td>
</tr>
</tbody>
</table>

**Table 7-4: Female volunteer drivers selected for experiment 2 (below 50)**
### Male Subjects over 50

<table>
<thead>
<tr>
<th>ID</th>
<th>Age</th>
<th>Ht. (cm)</th>
<th>Wt. (kg)</th>
<th>Gender</th>
<th>Glasses</th>
<th>Hair style</th>
<th>Beard/ Shave</th>
<th>Moustache</th>
<th>Cap</th>
<th>Driving exp.</th>
</tr>
</thead>
<tbody>
<tr>
<td>MM01</td>
<td>54</td>
<td>180</td>
<td>80</td>
<td>M</td>
<td>Yes</td>
<td>Flat grey 4cm</td>
<td>Shaved</td>
<td>No</td>
<td>No</td>
<td>37</td>
</tr>
<tr>
<td>MM02</td>
<td>50</td>
<td>175</td>
<td>76</td>
<td>M</td>
<td>Yes</td>
<td>Grey curly 3cm</td>
<td>Shaved</td>
<td>Yes</td>
<td>No</td>
<td>20</td>
</tr>
<tr>
<td>MM03</td>
<td>51</td>
<td>178</td>
<td>75</td>
<td>M</td>
<td>No</td>
<td>Curly 2cm</td>
<td>Shaved</td>
<td>No</td>
<td>No</td>
<td>30</td>
</tr>
<tr>
<td>MM04</td>
<td>62</td>
<td>167</td>
<td>73</td>
<td>M</td>
<td>Yes</td>
<td>Bald</td>
<td>Shaved</td>
<td>No</td>
<td>No</td>
<td>35</td>
</tr>
<tr>
<td>MM05</td>
<td>56</td>
<td>172</td>
<td>85</td>
<td>M</td>
<td>Yes</td>
<td>Short grey</td>
<td>Shaved</td>
<td>No</td>
<td>No</td>
<td>38</td>
</tr>
</tbody>
</table>

Table 7-5: Male volunteer drivers selected for experiment 2 (above 50)

### Female Subjects over 50

<table>
<thead>
<tr>
<th>ID</th>
<th>Age</th>
<th>Ht. (cm)</th>
<th>Wt. (kg)</th>
<th>Gender</th>
<th>Glasses</th>
<th>Hair style</th>
<th>Beard/ Shave</th>
<th>Moustache</th>
<th>Cap</th>
<th>Driving exp.</th>
</tr>
</thead>
<tbody>
<tr>
<td>FF01</td>
<td>55</td>
<td>160</td>
<td>52</td>
<td>F</td>
<td>Yes</td>
<td>15cm grey black</td>
<td>N/A</td>
<td>N/A</td>
<td>No</td>
<td>37</td>
</tr>
<tr>
<td>FF02</td>
<td>53</td>
<td>175</td>
<td>57</td>
<td>F</td>
<td>No</td>
<td>20cm grey white</td>
<td>N/A</td>
<td>N/A</td>
<td>No</td>
<td>34</td>
</tr>
<tr>
<td>FF03</td>
<td>50</td>
<td>165</td>
<td>87</td>
<td>F</td>
<td>Yes</td>
<td>20cm Black</td>
<td>N/A</td>
<td>N/A</td>
<td>No</td>
<td>25</td>
</tr>
<tr>
<td>FF04</td>
<td>52</td>
<td>165</td>
<td>86</td>
<td>F</td>
<td>No</td>
<td>20cm Black</td>
<td>N/A</td>
<td>N/A</td>
<td>No</td>
<td>28</td>
</tr>
</tbody>
</table>

Table 7-6: Female volunteer drivers selected for experiment 2 (above 50)
7.3.7. Conclusion of experiment 2

Experiment 2 was conducted after repositioning of the IRISYS thermal imager, change of test rig and other modifications to the tracking algorithm. The volunteer drivers and driving scenarios are carefully selected based on the information required. It can be said that this experiment shows the true tracking posture capabilities of the IRISYS thermal imager. The tracking algorithm is able to identify eighteen (18) different posture movements which are noteworthy. Real driving video comparisons and installing and analysing the safety system in a real car were done afterwards. No major changes to the imaging algorithm and artificial neural network were done after this experiment.
7.4. **Real life video data comparison**

Video footage was obtained of 20 volunteer drivers driving in an urban area and later onto a motorway. Out of 20, 10 volunteers were below the age of 45, whereas the other 10 volunteers were over the age of 55. Volunteers were selected as 50% male and 50% female. Each video lasts for at least 45 minutes depending upon each volunteer’s driving time from point A to point B.

A conventional method of video experiment study was used which involved professional video equipment, log book and stopwatch usually built-in the recording equipment. This method is mostly used by ergonomists for various studies. The process involves a tedious sequence of going through the experimental videos in slow motion back and forth and recording driver’s movements in the log book together with the time taken to complete the driving task. The equipment used for analysing the videos was professional editing equipment Sony SVO-9620 (see Figure 7-25).
The log created was later compared to the generated p-code, the results of which are explained in the section 8.3.
7.5. Experiment 3: Real car experiment using infrared imager

7.5.1. Aim of the experiment

Previous experiments in driving simulators and video footage comparison with actual driving behaviour showed a well developed and stable safety system. Therefore the aim of this experiment was to implement the IR imaging system in a real car. The data would still be processed offline. Trunk stability data collection was also possible from this experiment, due to the inertial forces being present. These inertial forces were non-existent in the driving simulator experimentation. This was the last experiment in a series of experiments conducted during this research.

7.5.2. Peugeot 406 driving in controlled area

The vehicle selected for experiment was a Peugeot 406 Estate car which is shown in Figure 7-26.
The experiment conducted (shown in Figure 7-27) consisted of three trial runs. These trials were required to obtain trunk stability results which are shown in section 8.6.2. These trials are as follows:

- Trial run 1: Normal driving
- Trial run 2: Moderate trunk stability
- Trial run 3: Severe truck instability (to represent an older or disabled driver)
Each experimental trial run consisted of going through a test route and completing certain driving tasks. These driving tasks were as follows:

- Negotiate a roundabout
- After 30 yards turn left
- Stop at T-Junction, check both sides for traffic
- Make a right turn
- Follow the road for 100 yards
- Follow the road round a left turn
After 50 yards, stop and signal for a right turn

Check the rear view mirror and side mirror for traffic

Make a right turn

Follow the road for another 50 yards and stop

Reverse park the car into a parking bay.

7.5.3. Mounting of IR Imager

A specialised stand was used for mounting the IRISYS thermal imager see Figure 7-28. This stand ensures that the imager is mounted securely and does not move while the vehicle is in motion.
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Figure 7-28: Specialized stand used for mounting IRISYS thermal imager inside the vehicle

**Inverter**

Supplying power to the IRISYS thermal imager and Data acquisition platform was also an issue. An inverter shown in Figure 7-29 was used for this purpose. It takes 12 DC Volts at 13 Amperes from a cigarette lighter and supplies 240AC Volts at 150 Watts to the devices.
7.5.4. Data Acquisition platform

The Data acquisition platform was a laptop with a serial port (COM 1) and with Data acquisition software installed. The experimental trials were conducted at 2 FPS. No visual camera or webcam was mounted with the IRISYS thermal imager as the algorithm had already been tested in experiment 2, see section 7.3.
7.5.5. Volunteer drivers

Not many volunteer drivers were required at this stage as the safety system algorithm had been tested and evaluated before. Therefore only an individual driver carried out the trial runs whose results are shown in section 8.5.

7.5.6. Conclusion of experiment 3

Experiment 3 was the last series of experiments conducted for this research. The first two experiments were the development stage for the algorithm. The third experiment used the safety system implemented in a real car, thus showing the safety system capability in its working environment.
7.6. Summary

- The aim of the first experiment was to find the capabilities of the IRISYS thermal imager.

- The second experiment repositioned the IRISYS thermal imager and changed to a different test rig for better flexibility. This experiment was significantly large in terms of number of volunteers and the number of trial runs each volunteer was asked to conduct.

- The safety system algorithm developed and tested on data from the second experiment was capable of identifying detailed posture, movement and behaviours. This accomplished the guidelines for the safety system.

- Driving video comparison was conducted by using special purpose video editing and playback equipment.

- The third experiment was conducted in a real car (Peugeot 406). To show that the safety system can be implemented without major problems in practice. The car was taken for three trial runs. The results are shown in Section 8.5.
8. Results and discussion

8.1. Introduction

This chapter is divided into two sections. The first section shows the results from the experiments that were conducted. The results are mostly in the form of graphs which are the output of neural network simulations. The later section assesses the capabilities of the safety system by considering different driving situations and everyday driver problems.

8.2. Results of Neural network as a behaviour modeller

In the following pages the reader will see graphs (from Figure 8-1 to Figure 8-3) that show the simulated results of the neural network. These results shown below are for a single volunteer driver, the algorithm used is described in Section 5.2.2 and the data collected from Experiment 2 is detailed in Section 7.3. The complete results for 20 volunteer drivers are shown in Appendix A.
Figure 8-1: Head region FBN neural network simulation result
Figure 8.2: Torso region FBN neural network simulation result

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Figure 8.3: Shoulder and arm region FNN neural network simulation result.

Number of samples: 0 1 5 9 13 17 21 25 29 33 37 41 45 49 53 57 61 65 69 73 77 81 85 89 93 97

Hands on steering

Hands off steering
8.3. **Real life data comparison of results**

The video footage of each volunteer was analysed by taking movement description, time taken and the p-code was judged and noted. A certain pattern of movements relates to the p-code generated during the video analysis. The movement for each motion detected can be small, like looking right, or could be a series of movements to carry out a particular manoeuvre, like putting a seat belt on. This series of movements will create a pattern for that manoeuvre which is more or less the same for most drivers. Some of the patterns of motion with p-codes follow. The large manoeuvres are broken down into smaller movements which the safety system detects, see Table 8-1.
<table>
<thead>
<tr>
<th>Driving task</th>
<th>Time</th>
<th>P-Code</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Putting Handbrake</td>
<td>2 s</td>
<td>D-L-S</td>
<td>One hand on steering wheel</td>
</tr>
<tr>
<td>2 Left Turn (T-Junction or Cross Road)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Look Right</td>
<td>3 s</td>
<td>N-R-S</td>
<td>Less traffic</td>
</tr>
<tr>
<td>Turn Left (Driver looks ahead)</td>
<td>1 s</td>
<td>N-F-S</td>
<td></td>
</tr>
<tr>
<td>3 Left Turn (T-Junction or Cross Road)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Look Right</td>
<td>6 s</td>
<td>N-R-S</td>
<td>Heavy traffic from right</td>
</tr>
<tr>
<td>Turn Left (Driver looks ahead)</td>
<td>1 s</td>
<td>N-F-S</td>
<td></td>
</tr>
<tr>
<td>4 Merge onto Motorway</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Looks at speedometer</td>
<td>0.5 s</td>
<td>N-F-S</td>
<td>Small movement undetected by the system</td>
</tr>
<tr>
<td>Rear View mirror</td>
<td>0.5 s</td>
<td>N-F-S</td>
<td>Small movement undetected by the system</td>
</tr>
<tr>
<td>Looks right</td>
<td>1 s</td>
<td>N-R-S</td>
<td>On slip road – checking blind spot</td>
</tr>
<tr>
<td>Looks ahead</td>
<td>1 s</td>
<td>N-F-S</td>
<td>On slip road – should be indicating</td>
</tr>
<tr>
<td>Looks right</td>
<td>1 s</td>
<td>N-R-S</td>
<td>On slip road – checking blind spot</td>
</tr>
<tr>
<td>Looks right – Lane Change</td>
<td>1 s</td>
<td>N-F-S</td>
<td>On Motorway</td>
</tr>
</tbody>
</table>

Table 8-1 Real life driving task comparison with neural network result
Tasks vary considerably in their complexity and also according to the driving situation at the time. In future multi-sensor fusion will help to identify and categorise particular tasks. For example, the difference between merging onto a motorway and turning into a junction or roundabout can be found by linking the speedometer with the current IR system. This will tell the system when the car is stopped, or moving very slowly, at a junction, signal or roundabout; otherwise if the car is moving and the driver looks in a certain direction aggressively two or three times it would indicate a change of lane or merging onto a motorway.

8.4. Use of P-codes in intelligent central safety control

Intelligent central safety control is a device installed in an intelligent car which combines all intelligent safety systems and intelligent sensors (see Figure 8-4). This control unit takes processed information from each safety system and sensor like P-codes, throttle inputs, braking data and tyre pressures. It will create a complex network of vehicle data flowing between the control unit, safety systems and sensors.
This central safety control will be capable of identifying even the smallest driving tasks and determining the risk in a driver’s driving pattern. Consider a multi-channel input of information coming to the intelligent central safety control (see Figure 8-5). Some information will be needed as instantaneous or single-frame data and some will need to be acquired over a period to provide a time history for analysis. Each channel provides useful information to the safety control unit and based on that the control unit will be able to decide the driving pattern, risk involved and safety precautions that will be required. This is beyond the scope of this research therefore the concept is only discussed briefly here.
8.5. **Real car experimentation results**

Experiment 3 was conducted in a Peugeot 406 car. The neural network simulation results of this experiment are shown in Figure 8-6, Figure 8-7 and Figure 8-8. The details of experiment 3 are explained in Section 7.5.
Figure 8-6: Head region FBN neural network results
Figure 6-7: Torso region FRN neural network results

Ann simulation response

Number of samples

Looking right
Looking ahead
Looking left
Figure 8-8: Shoulder and arm region FNN neural network results

Ann simulation response

Number of samples

—— Hands on steering

—— Hands off steering

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Figure 8-6 (for region R1), Figure 8-7 (for region R2) and Figure 8-8 (for region R3) show the results of simulated neural networks from the real car experiment. These figures show results with similar accuracy to that of the driving simulator experiment. Since the safety system was installed in a real car and the results are of the same accuracy to that of experiments conducted in the driving simulator it can be said that the safety system can be installed in a real car without any difficulty.

8.6. Assessing capabilities of the system

A list is made of what to expect from the system and what cannot be expected from the system. The list is broken down into ‘achievable’, ‘unachievable’ and conditional’. The ‘achievable but conditional’ list can be achieved only if further work is accomplished.

Achievable

- Trunk stability

- Airbag deployment
  - Out of position
  - Large or small person
  - Distance from steering wheel
  - Eye Height for airbag deployment

- Eye Height as visibility issue

- Head turning

- Dynamic allocation of attention /Driver distraction
  - Talking / attending to passenger
  - Mobile phone usage
  - Lighting up cigarette
  - Adjusting radio or cassette / CD player
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- Other activities in car / looking down

**Achievable but conditional**
- Drowsiness and fatigue: physical indicators
- Reaction time
- Tunnel vision
- Movement time / trajectory
- Time period with attention away from road: physical indicators
- Impairments
  - Drug abuse

**Unachievable**
- Task management
- Fatigue or sleep deprivation – cognitive effects, eye movements and small movements.
- Impairments
  - Detection of alcohol
- Cold legs and feet in third age people
- Not wearing seatbelt
- Time Period with attention away from the road – cognitive factors or small movements.
The scenarios discussed below were analysed and altered manually to show the safety system other capabilities. The achievable capabilities of the safety system are discussed in further detail below:

### 8.6.1. Drowsy driving (Nodding off at steering wheel)

From the literature review it can be said that sleep or drowsiness can be very critical while driving (see section 2.1.4). It can not only be dangerous for the driver but for other people on the road at that time as well. Symptoms of sleepiness can be identified by nodding, yawning, eye alertness and task focus. When driving for longer periods without interruptions or driving during the times of 11pm to 7am the driver starts to get drowsy. While in the sleepy state the critical symptom is nodding off at the steering wheel. It involves an instant of sleep during which the head drops forward then head lunges upwards and comes back to the driving position in an erratic motion. This behaviour was observed during Experiment 2, scenario 3 and is familiar to many people.

The following work plan in Figure 8-9 and analysis shows how movement and posture detection system can identify nodding while driving.
Analysis and discussion

The movement and posture detection system was installed in car simulator. Experiments were conducted; the scenario used in these experiments was over 45 minutes and included a long stretch of straight road. The long stretch of road or rural driving is known to cause drowsiness if driven for longer periods of time. The infrared field of view in the experiment is approximately 350mm by 350mm. The infrared image when interpolated is 120 pixels by 120 pixels. This means that a driver moving his head by about 7 pixels is equivalent to 20 mm approximately.

Drowsy driver was detected by the system as a leaning posture. If the movement information from the system is linked with time history a certain pattern of nodding can be seen. The nodding pattern can be similar to the head to lean for fifteen (15) to thirty-five (35) degrees. The driver usually moves back from nodding position to normal driving position in an erratic motion. This sleep driving pattern is repetitive and nodding occurs randomly in a short time frame.
It can be seen from the Figure 8-10 that during the 45 minutes of experiment a female subject nodded off. The first frame showed a normal driving position and the nth frame her head lunges upwards.

8.6.2. Tiredness and fatigue

Although it is not possible to detect cognitive signs of fatigue or small movements some repeated physical actions can be a sign of fatigue. For example, in Figure 8-11 driver is shown touching her face. This could be a sign for fatigue and tiredness if the driver is driving for over an hour, at night time or other conditions linked with driver fatigue and tiredness. If this information is correlated with time history, the safety system can make assumptions with much accuracy.
8.6.3. Trunk stability

Trunk stability affects racing drivers and average on-road drivers. But for racing drivers this effect is relatively higher than road drivers. The third age drivers have frail bodies therefore truck stability will have considerable effect. Especially Third age drivers are unstable in cars when going around the corners. Their trunks sway sideways due to inertial forces (Treffner et al., 2002).

The safety system is able to identify the trunk stability effect if time based analysis is conducted. Time based analysis involves the study of IR thermographs and p-codes over a period of time. For example if the driver is swaying unnecessarily over a certain time frame can be identified as unsafe due to trunk instability. Figure 8-12 shows an average driver going around a roundabout.
Figure 8-12: Stable driver's trunk swaying effect while going over roundabout. Black line shows trunk swaying angle.

Figure 8-13 and Figure 8-14 shows unstable trunk drivers going around a roundabout.

Figure 8-13: Moderately unstable driver's trunk swaying effect while going over roundabout.

Black line shows trunk swaying angle.
Figure 8-14: Highly unstable driver’s trunk swaying effect while going over roundabout. Black line shows trunk swaying angle.

Figure 8-15 shows trunk stability driving pattern based on time history. During driving the driver keep repeating the movement often making the safety system identify the posture as trunk stability based on time history instead of leaning posture.
The following sections discuss problems which require single frame analysis.

8.6.4. Out of position driver

Identifying out of position (OOP) driver is a crucial task as far as safety is concerned. Low resolution infrared imaging can classify OOP drivers. To make the images clear to the visible eye the images shown are interpolated and infrared images are thresholded up to four (4) levels see Figure 8-16, Figure 8-17 and Figure 8-18.
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Figure 8-16: Normal driving position taken by infrared imager

It can be seen that information in Figure 8-17 and Figure 8-18 are easier to decode visually than Figure 8-16.

Figure 8-17: Normal driving position in Interpolated Infrared image
Figure 8-17 and Figure 8-18 shows a driver in normal driving conditions. Figure 8-19 shows a person leaning down at driving seat in a car simulator. From the Figure 8-19 it can be observed that the driver's head is outside the field of view and leaning towards the steering wheel. It can be assumed that the driver could be reaching for something on the passenger side. This is a very dangerous position if the airbag deploys and can cause serious injuries particularly to the driver. To make the system more flexible and worthwhile further information can be input into the system for example speed of the vehicle and time driver was in leaning down position.
The driver position in Figure 8-20 is similar to Figure 8-19 but the situation is slightly different. In Figure 8-20 the supposition of worst case scenario is considered; that the driver attention is away from the road. It could be because the driver concentration is on the dashboard console or he is trying to use a car radio or CD player. Again the further information from the time history for example how long the driver was in this position, road will corroborate the system.
Driver is putting seat belt on in Figure 8-21. At this instant driver took his hands off the steering wheel and looking down while leaning left towards the seat belt buckle. Identification of drivers which reverse by looking directly at rear window is also possible for example reverse parking or parallel parking. The major difference between Figure 8-21 and reversing will be that the driver hands will be on the steering wheel. In either of these two cases the airbag need not be deployed as both tasks are for slow motion or stationary vehicle. If airbag is deployed there will be a danger of neck injury to the driver. The severity of injury will depend upon the physical built of the driver.
Small height of drivers is considered a safety concern, if their seats are not adjusted appropriately. The appropriate eye height varies from individual to individual but as a rule of thumb the eye height should be higher than the steering wheel (Porter et al., 2001).

The eye height of the driver is calculated by finding the centroid of the driver’s face. If the driver height is below a certain limit the complete head is displayed in the IR FOV. Thus a centroid can be found after segmentation and eye height can be approximately calculated. If the driver’s height is above a certain limit then the eye height need not to be calculated as tall drivers do not face this risk. Therefore measuring eye height requires that the driver’s seat is adjusted appropriately, which is shown in Figure 8-22.
8.6.6. Head turning and dynamic allocation of attention while driving

Dynamic allocation of attention includes several tasks that driver performs unintentionally. These tasks are unsafe and a risk to driver, passengers and pedestrians such as talking to passenger face to face, looking outside the side window at an accident or advertisement board, using a mobile phone or a GPS system and frequent looking at the speedometer while driving in a speed camera zone. Not all dynamic allocation of attention can be detected using the safety system only particular ones that involve turning of head and leaning like talking with passengers face to face or looking outside the side windows. Some examples of dynamic allocation of attention that could not be detected by the safety system are small head movements for looking at the side mirrors and rear view mirror, eye gaze at the traffic coming from the side without turning the head and small head movement made to look at the GPS display or CD player display at dashboard.

Stiff neck in older drivers and sports injury drivers could not be detected but driver head movement can be monitored. For example, if the driver did not look towards right for some time or when making a turn at T-junction shows that the driver might
have restricted neck movement. Another example is failure to look at blind spot due to stiff neck while merging onto a motorway.

Head turning is a common body motion when driving a car. For example when crossing an intersection, going through roundabouts, making turns and stopping at T-Junctions, all these driver’s tasks require head movement to left or right. Most of these driving tasks are done when the car is stationary. Driver glancing for a fraction of a second to left or right is permitted during driving but looking left or right for longer than two (2) seconds is classified as hazardous driving (Klauer et al., 2006).

The scenario is shown in Figure 8-23, a third age driver is looking down for over two and half (2.5) seconds at the traffic signal.

![Interpolated Infrared Image](image1.png) ![4 Level thresholded Infrared Image](image2.png)

Figure 8-23: 65 Year old driver concentrating/looking down left at gear over 3 seconds

The driver was trying to change to lower gear before he moves off from the traffic signal. The driver was driving in the car simulator therefore posed no such threat. But this kind of driver’s lapses when driving on actual road can put the driver and other people on road at risk.
8.6.7. Driver characteristics or distinct features

The infrared imager can identify drivers with different characteristics. Driver while smoking can be prominent without difficulty using infrared imagery as shown in Figure 8-24. A hot spot is noticed in Figure 8-24 which shows the flame of the cigarette. In another situation (see Figure 8-25) driver is seen using a mobile phone. In Figure 8-25 driver is shown holding one hand close to his ear for several seconds while driving. This will not always be the case as hands free kits are common nowadays. This can be advantageous as the system under consideration will spot drivers using mobile phones without hands free kit. As previous research shows that using mobile phones without hands free kit is as precarious as driving under the influence of drugs or alcohol.

Figure 8-24: Driver smoking (Front view)
In addition to classifying diverse postures and positions the system can obtain information about the physical build of a driver without intruding on their privacy. For example in Figure 8-26 there is a substantial difference between slim build and muscular build of drivers. The hottest area in the infrared image in Figure 8-26 is the frontal face area. For a muscular built person the frontal face area increases significantly, approximately twice as that of slim built one.
Average built drivers are shown in Figure 8-27. The frontal face area is approximately equal for both drivers. The hair length can sometimes differentiate between some drivers, for example most female drivers have longer hair than male drivers. Based on this assumption the airbag and other automotive secondary safety systems can acquire information about the driver gender and build.
To accommodate 95 percentile design for intelligent airbags and other safety system the driver height can also be very useful. Tall and short persons can be identified, as the field of view for infrared imager stays constant (see Figure 8-28). This will not hamper the other capabilities of the system for that particular driver, for example identification of driver position and behaviour.
8.6.8. Distance from steering wheel

The distance from steering wheel to driver can be measured by using image processing and optics calculations. Mounting of the infrared imager is shown in Figure 8-29. The angle between the driver and Infrared imager facilitate the measurement of steering wheel and the driver positions.
Figure 8-29: Steering distance measurement using IR Imager
Now by using Figure 8-30 where 'A' is the distance between the steering and thermal imager and 'z' is an image plane parallel to the thermal imager FOV. Then 'D' and 'x' can be found by the following expression:
\[ A = C \times \sin 30^\circ \]
\[ C = \frac{A}{\sin 30^\circ} \]
\[ D = C \times \cos 30^\circ \]
\[ D = \frac{A}{\sin 30^\circ \times \cos 30^\circ} \]
\[ D = \frac{A}{\left(\frac{1}{2} \times \sqrt{3} / 2\right)} \]
\[ D = \frac{4A}{\sqrt{3}} \]

Assume \( \phi \approx 30^\circ \)

\( Z \) is \( x \) world coordinate from the thermal imager

\[ \therefore X = Z \times \cos 30^\circ \]
\[ X = \frac{\sqrt{3}}{2} \]

\[ \therefore (D + x) = 2ZA \] \hspace{1cm} (Equation 7)

To calculate the field of view area covered by the infrared imager the following calculation was used (see Figure 8-31).

\[ \tan \theta = \frac{\text{fov1}}{D} \]

Where
\[ \theta = 10^\circ \]
\[ D1 = 1 \text{ metre} \]

\[ \text{fov1} = D1 \times \tan \theta \]
\[ \text{fov1} = 1 \times \tan(10) \]
\[ \text{fov1} = 0.1763 \]
\[ FOV = \text{fov1} \times 2 \]
\[ FOV = 0.352 \text{ square metre} \]
Figure 8-31: FOV area calculation

Figure 8-32 shows the FOV calculation of infrared thermal imager; the double sided arrows in the figure give an idea about the distance. The distance of one metre is an approximation. The infrared image on the left shows the driver driving very close to the steering wheel.

Figure 8-32: Infrared images showing distance from steering wheel
8.6.9. Special scenarios

Lane merging hazard in third age

This particular situation is selected because it is a high risk involved for older drivers due to their restriction of movement and slow reaction time.

- Sixty year old driving at night time in vehicle A.
- While merging onto a motorway
- Heavy vehicle passing and decided to give way to the heavy vehicle by checking side mirror
- Tried to pull in behind heavy vehicle, but fail to check blind spot which comes under driving lapses (see section 2.1.7 for third age driver problems).
- The vehicle B just behind the heavy vehicle, which driver in Vehicle A fail to notice. Unless the driver in vehicle B adjusts the speed there could be a chance for accident.

Restriction of neck movement can be a single issue not only in third agers. But it can even be a professional driver with neck strain. These kinds of movements can be identified by the safety system if time based history method is used which is explained in section 8.6.2.

Multiple drivers

Young drivers are at elevated risk when accompanied by multiple passengers. The risk increases 4-5 times, than driving alone. The safety system if installed in a different position or wider angled lens can detect multiple passengers in a car.
8.6.10. Discussion

The safety system is shown that it can identify eighteen different driver movements and interpret it into p-codes. Also the safety system capabilities can be enhanced with some modifications. It is capable of identifying drowsy driver and trunk stability if time history based analysis is conducted. On the other hand OOP driver, eye height and driver's physique can be detected by adding another imaging algorithm. Trigonometric calculations in section 8.6.8 showed that the distance from the steering wheel to the driver can be found using IR thermographs. Head turning has been identified using p-codes.

The safety system cannot detect small movements of driver's head and eye gaze. Eye gaze can be anything from looking in the side and rear view mirrors to scenes on the road. Since the thermal imager is low resolution it is difficult to detect small movements made by the driver's head.

The IR safety system will be a part of intelligent central safety control. This safety system is a non-intrusive driver movement and position monitor. It is better than other methods which are either visual or contact based. The integration of IR safety system, low cost sensors, multi-sensor systems and existing sensors will make a complex safety network in the vehicle making intelligent cars even safer.

The initial focus of this research was, as the title states, on detecting problems typically encountered by third age drivers. As the work progressed it became apparent that means of detecting problems or high risk behaviours for third age drivers would also apply to drivers of any age, especially those with impairments due to disability, injury or simple tiredness. Therefore the research would inevitably have wider application than first thought. The third age theme was, however, maintained as a useful focus to direct the research, but the results have delivered an approach which can be beneficial for all drivers, irrespective of age. Future implementation of the system may therefore be described as 'inclusive design'.
8.7. Summary

- This chapter addresses the research questions that were generated at the start of research.

- It also evaluates the capability and potential of the safety system.
9. Conclusions and Further work

9.1. Conclusions

- The contribution to knowledge made by this thesis includes the identification of driver postures, movements and behaviour, use of a low resolution IR imager as an intelligent vehicle safety system and a novel design of a neural network used for thermal imaging.

- This thesis studies driver problems and current automotive safety systems and highlights the fact that no safety system exists nowadays that can identify driver postures, movements and behaviours which may pose a high level of risk to the driver. Such a safety system is especially required by third age people and disabled drivers due to physical and cognitive impairments.

- Infrared imaging has been shown to provide a successful, non contact and non intrusive method for identifying driver movement and postures. The IRISYS thermal imager selected as the primary sensor is relatively low cost and low resolution, offering advantages in terms of driver privacy. It has been shown to provide very robust performance over a wide range of conditions.

- An algorithm has been developed based on thermal image processing techniques and a novel neural network design. The algorithm was verified on a series of experiments and was shown to be robust.

- Experimentation has been conducted in a simulated environment using the STISIM car simulator system and later in a ‘Peugeot 406’ car. The data acquisition was conducted using software custom-built in Lab/Windows CVI.
The experimentation involved a wide spectrum of human subjects from 16 years old to 67 years old. The scenario for experimentation involved urban as well as rural runs. The system had therefore been tested with a wide range of variables.

- The main focus of the work on third age drivers subsequently delivered an approach that is inclusive and can ultimately be beneficial to all drivers at times irrespective of age.

- The safety system as developed using the IRISYS thermal imager and the algorithm is able to identify eighteen different driver postures and movements. Several other general and special driving cases that are high risk for the driver were also identified using the same technique.

### 9.2. Further work

- Driver posture and movement is a very complex task. It varies from individual to individual. Therefore a detailed study of driver posture and movement related to high risk situations is required.

- Extending the safety system implementation and experiment from cars to large commercial vehicles which include public buses and trucks would be beneficial. This will allow the detection of fatigue and other problems in professional drivers and hence increase the safety of commercial vehicles.

- The safety system can be extended as a tool for helping ergonomists for studying driver’s behaviour by video. The conventional method of studying driver videos includes tedious work of long hours of manual playback and noting each driver task with respect to time. The system can be used to detect driver behaviour and show only the useful behaviour at the user’s request.
• Further improvement in the safety system can be achieved by sensor fusion. For example fusing with a visual camera which tracks eye pupil movements. This will allow more advanced movement and posture detection and prediction.

• Implementing novelty detection techniques will improve the artificial neural network. Novelty detection will make the system more robust when unrecognised things are displayed to the neural network.

• Real-time training of the artificial neural networks can be implemented. This will improve the safety system prediction and accuracy significantly as the safety system will be training while taking the system offline.

• On the physical design side, improving the packaging of the IRISYS thermal imager is required so that it can be installed in a vehicle with ease.

• The imaging algorithm and ANN should be implemented in embedded form, thus eliminating the need for offline data collection and analysis.
10. References


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Appendix A: Result graphs from ANN

Region 1 - Head region

- Normal head position
- Leaning head position
- Looking down head position

Number of samples

0 0.5 1 1.5 2 2.5 3 3.5

R1

Intelligent Automotive Safety Systems: The Third Age Challenge
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Cl
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R1

2.5+-----~----~--------------~--~----------------~--~~------~~

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2

1.5+---------------~--~--~--------------------------~----~~----~----~

co<

0.5+---~--~--~------~--~------------~----------~--------------~

5 9 13 17 21 25 29 33 37 41 45 49 53 57 61 65 69 73 77 81 85 89 93 97

Number of samples

Ann simulation response

Normal head position
Leaning head position
Looking down head position

Intelligent Automotive Safety Systems: The Third Age Challenge
Cl

III

Co.

III

I!

ccc et

O.5+

R1

- - - Leaning head position

- - - Looking down head position

Number of samples

1 5 9 13 17 21 25 29 33 37 41 45 49 53 57 61 65 69 73 77 81 85 89 93 97
Number of samples

Ann simulation response

- Normal head position
- Leaning head position
- Looking down head position

Intelligent Automotive Safety Systems: The Third Age Challenge
Ann simulation response

Number of samples

- Normal head position
- Leaning head position
- Looking down head position

Intelligent Autonomous Safety Systems: The Third Age Challenge
R1

Number of samples

<table>
<thead>
<tr>
<th>Ann simulation response</th>
<th>3.5</th>
<th>3</th>
<th>2.5</th>
<th>2</th>
<th>1.5</th>
<th>1</th>
<th>0.5</th>
<th>0</th>
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<tbody>
<tr>
<td>Normal head position</td>
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<td>Leaning head position</td>
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<td>Looking down head position</td>
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</tbody>
</table>

Intelligent Automotive Safety Systems: The Third Age Challenge
R1

Number of samples

Amn simulation response

- Normal head position
- Leaning head position
- Looking down head position
R1

- Normal head position
- Looking down head position
- Leaning head position

Number of samples

Amplitude response

0 0.5 1 1.5 2 2.5 3 3.5

1 5 9 13 17 21 25 29 33 37 41 45 49 53 57 61 65 69 73 77 81 85 89 93 97
R1

Number of samples

Ann simulation response

- Normal head position
- Leaning head position
- Looking down head position
Intelligent Autonomous Safety Systems: The Third Age Challenge
REGION 2 – Torso region

- Looking right
- Looking ahead
- Looking left

Number of samples
R2

Looking right
Looking ahead
Looking left

Number of samples

0 0.5 1 1.5 2 2.5 3 3.5

Ann simulation response

Number of samples
Looking right
Looking ahead
Looking left
Intelligent Automotive Safety Systems: The Third Age Challenge
The graph shows the ANN simulation response over the number of samples for R2. The simulation responses are categorized into three groups: looking right, looking ahead, and looking left. The response values range from 0 to 3.5, and the number of samples is indicated from 1 to 97.
R3

Number of samples

Ann simulation response

- - - Hands on steering

- - - Hands off steering

Intelligent Automotive Safety Systems: The Third Age Challenge
The graph shows the number of samples over time for two conditions:

- **Hands on steering** (dashed line)
- **Hands off steering** (solid line)

The x-axis represents the number of samples, ranging from 1 to 97. The y-axis represents the annulation response, with values from 0 to 2.5.
R3

Number of samples

0 1 5 9 13 17 21 25 29 33 37 41 45 49 53 57 61 65 69 73 77 81 85 89 93 97

Hands on steering

Hands off steering
R3

Number of samples

Annulation response

Hands on steering
Hands off steering
R3

Number of samples

Hand simulation response

Hands on steering
Hands off steering

Intelligent Automotive Safety Systems: The Third Age Challenge
R3

Number of samples

Ann simulation response

- - - Hands on steering

- Hands off steering
R3

Number of samples

Ann simulation response

--- Hands on steering
--- Hands off steering

Intelligent Automotive Safety Systems: The Third Age Challenge
R3

Number of samples

Ann simulation response

- - Hands on steering
- - Hands off steering
R3

2.5
2
1.5
1
0.5
0

Number of samples

-- Hands on steering
--- Hands off steering
Appendix B: MatLAB Code

This appendix describes the important function that were written during this research. These functions are written in MatLAB M-Code language.

1. The ReadIquire2gui.m function reads the DAT files created by the Data Acquisition software for infrared, visual and internal thermal imager temperature data and imports it into MatLAB work space.

```matlab
function [Iquire, file1, numberimg] = ReadIquire2gui

[filename, pathname] = uigetfile ( ... %Shows the user interface to read files & path name
    {'* .dat', 'I-Quire Files'; ...
    '*.txt', 'I-Quire txt files'; ...
    '*.*', 'All Files'}, ...
    'Pick a file');

file1 = [pathname, filename]; %Puts file and pathname together
ii_eof = 0;
i = 1;
fid = fopen(file1); %Opens File
if fid == -1
    while ii_eof <= 0
        % Reads Infrared data
        a = fgetl(fid);
        b = sscanf(a, '%d');
        Iquire(i).Infrared = reshape(b, 16, 16); % Arranges IR data into a 16x16
        Iquire(i).Infrared = Iquire(i).Infrared / 10; % divides the multiple of Infrared by 10
        % Reads Internal temperature
        c = fgetl(fid);
    end
    Iquire(i).Internal = [c, 32]; % These three lines below get Internal temperature of IRISYS & put in a data
end
```
2. The **CompareIQ2.m** (see Figure C-1) function reads the infrared data from the DAT file and compares the infrared thermograph before and after image processes. The GUI interface go through the experimental data easily and quickly and can import data to MatLAB workspace with ease.
% This Function executes on slider movement.

function slider2_Callback(hObject, eventdata, handles)
    handles.slider_value = fix(get(handles.slider2, 'Value'));  % GETS SLIDER VALUE
    axes(handles.infrared);
    infl = fliplr((handles.iq(handles.slider_value).Infrared));
    handles.infl28 = interp2(infl, 3);
    rl = handles.infl28(1:80, 1:61);  %Section for R1 - TORSO
    rl_b = rl > 30.5;
    rl_area = sum(sum(rl_b));  %area rl

    r2 = handles.infl28(1:80, 60:121);  %Section for R2 - HEAD
    r2_b = r2 > 30.5;
    r2_b = bwareaopen(r2_b, 200);
    r2_area = sum(sum(r2_b));  %area r2
r2_b=bwlabel(r2_b);a=regionprops(r2_b,'orientation'); %finds angle for head
r2_aa=r2_area/a.Orientation; %area/angle r2

r3=handles.infl28(81:121,:); %Section for R3 - ARM / SHOULDER
r3_b=r3>27;
r3_area=sum(sum(r3_b)); %area r3

imagesc(interp2(infl1,3));
colormap('gray');

%now being used for cropped region
axes(handles.r1);
imagesc(r1_b); % displays r1 file
axes(handles.r2);
imagesc(r2_b); % displays r2 file
axes(handles.r3);
imagesc(r3_b); % displays r3 file

handles.r1_area=r1_area;
handles.r2_area=r2_area;
handles.r2_aa=r2_aa;
handles.r3_area=r3_area;

set(handles.edit3, 'String', handles.r1_area);
set(handles.edit4, 'String', handles.r2_area);
set(handles.edit5, 'String', handles.r2_aa);
set(handles.edit6, 'String', handles.r3_area);

set(handles.edit2, 'String', handles.slider_value);
guidata(hObject,handles);
3. The `annprocess.m` function reads data from the MS Excel XLS format files constructs, trains and simulates the ANN. Then writes the results in the same XLS file in appropriate space. The m-code is changed depending upon the network that is being trained.

```matlab
function annprocess

[filename, pathname] = uigetfile (...%Shows the user interface to read files & path name
    {'*.xls', 'Excel File'; ...
    '*.xls', 'Excel File'}, ...
    'Pick a file');
file1= [pathname, filename];  %Puts file and pathname together

%xls sheet1 =r1, sheet2 =aa r2, sheet3 =area r2, sheet4 = r3
%%%%%%%%%%%%%%%%%%%%R1 SECTION%%%%%%%%%%%%%%%%%%%%%%%

training_set1 = xlsread(file1,'sheet1','d2:d51');  %gets the first training set for r1
target_set1 = xlsread(file1,'sheet1','e2:e51');  %gets the first target set for r1
training_set2 = xlsread(file1,'sheet1','f2:f51');  %gets the second training set for r1
target_set2 = xlsread(file1,'sheet1','g2:g51');  %gets the second target set for r1
training_set3 = xlsread(file1,'sheet1','h2:h51');  %gets the third training set for r1
target_set3 = xlsread(file1,'sheet1','i2:i51');  %gets the third target set for r1

simulation_set1 = xlsread(file1,'sheet1','j2:j101');  %gets first simulation set for r1
simulation_set2 = xlsread(file1,'sheet1','l2:l101');  %gets second simulation set for r1
simulation_set3 = xlsread(file1,'sheet1','m2:m101');  %gets third simulation set for r1

training_set_r1 = [training_set1; training_set2; training_set3];
target_set_r1 = [target_set1; target_set2; target_set3];
simulation_set_r1 = [simulation_set1; simulation_set2; simulation_set3];
```
% FOR R1 ANN FF NETWORK

net_r1 = newff([r1_min r1_max],[2 1], Cof the o; % for R1 creates ANN FF network
net_r1.trainParam.epochs = 50;
net_r1.trainParam.goal = 0.01;
net_r1 = train(net_r1, training_set_r1, target_set_r1);

% Y = sim(net_r1, training_set_r1); % To simulate r1 training set enable this
output_set_r1 = sim(net_r1, simulation_set_r1); % simulates the ann ffb for r1

output_set1 = (output_set_r1(1:100))';
output_set2 = (output_set_r1(101:200))';
output_set3 = (output_set_r1(201:300))';

xlswrite(file1, output_set1, 'sheet1','k2:k101'); %write the first output set for r1
xlswrite(file1, output_set2, 'sheet1','m2:m101'); %write the second output set for r1
xlswrite(file1, output_set3, 'sheet1','o2:o101'); %write the third output set for r1

%%%%%%%%%%%%%%%%% R2 SECTION %%%%%%%%%%%%%%%%%%%%%

%%%% FOR AA

training_set1 = xlsread(file1,'sheet2','d2:d51'); % gets the first training set for r2
target_set1 = xlsread(file1,'sheet2','e2:e51'); % gets the first target set for r2
training_set2 = xlsread(file1,'sheet2','f2:f51'); % gets the second training set for r2
target_set2 = xlsread(file1,'sheet2','g2:g51'); % gets the second target set for r2
training_set3 = xlsread(file1,'sheet2','h2:h51'); % gets the third training set for r2
target_set3 = xlsread(file1,'sheet2','i2:i51'); % gets the third target set for r2

simulation_set1 = xlsread(file1,'sheet2','j2:j101'); % gets first simulation set for r2
simulation_set2 = xlsread(file1,'sheet2','k2:k101'); % gets second simulation set for r2
simulation_set3 = xlsread(file1,'sheet2','m2:m101'); % gets third simulation set for r2
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training_set_r2_aa = [training_set1; training_set2; training_set3];
target_set_r2_aa = [target_set1; target_set2; target_set3];
simulation_set_r2_aa = [simulation_set1; simulation_set2; simulation_set3];

%%%% FOR ANGLE

training_set1 = xlsread(file1,'sheet3','d2:d51'); % gets the first training set for r2
target_set1 = xlsread(file1,'sheet3','e2:e51'); % gets the first target set for r2
training_set2 = xlsread(file1,'sheet3','f2:f51'); % gets the second training set for r2
target_set2 = xlsread(file1,'sheet3','g2:g51'); % gets the second target set for r2
training_set3 = xlsread(file1,'sheet3','h2:h51'); % gets the third training set for r2
target_set3 = xlsread(file1,'sheet3','i2:i51'); % gets the third target set for r2

simulation_set1 = xlsread(file1,'sheet3','j2:j101'); % gets first simulation set for r2
simulation_set2 = xlsread(file1,'sheet3','k2:k101'); % gets second simulation set for r2
simulation_set3 = xlsread(file1,'sheet3','l2:l101'); % gets third simulation set for r2

training_set_r2_angle = [training_set1; training_set2; training_set3];
target_set_r2_angle = [target_set1; target_set2; target_set3];
simulation_set_r2_angle = [simulation_set1; simulation_set2; simulation_set3];

% FOR R2 ANN RB NETWORK

net_r2 = newrb(training_set_r2, target_set_r2, 0.01, 1); % for R2 creates a ANN RBN network, goal =0.01, spread = 1
% Y = sim(net_r2, training_set_r2); % To simulate r2 training set enable this
output_set_r2 = sim(net_r2, simulation_set_r2); % simulates the ann rbn for r2

output_set1 = (output_set_r2(1:100))';
output_set2 = (output_set_r2(101:200))';
output_set3 = (output_set_r2(201:300))';
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%write the first output set for r2
xlswrite(file1, output_set1, 'sheet2', 'k2:k101');
%write the second output set for r2
xlswrite(file1, output_set2, 'sheet2', 'm2:m101');
%write the third output set for r2
xlswrite(file1, output_set3, 'sheet2', 'o2:o101');

%%% R3 SECTION %%%% %%% %%% %%% %%% %%% %%% %%% %%% %%% %%% %%% %%%

% R3 SECTION % % % % % % % % % % % % % % % % % % % % % % % % % % % % % %

% R3 SECTION % % % % % % % % % % % % % % % % % % % % % % % % % % % % % %

% FOR R3 ANN FF NETWORK
net_r3 = newff([r3_min r3_max],[3 1], . In );
% for R3 creates ANN FF network
net_r3.trainParam.epochs = 50;
net_r3.trainParam.goal=0.01;
net_r3 = train(net_r3, training_set_r3, target_set_r3);
% Y = sim(net_r3, training_set_r3); % To simulate r3 training set enable this
output_set_r3 = sim(net_r3, simulation_set_r3); %simulates the ann ffb for r3

output_set1 = (output_set_r3(1:100));
output_set2 = (output_set_r3(101:200));

xlswrite(file1, output_set1, 'sheet4', 'k2:k101'); %write the first output set for r1
xlswrite(file1, output_set2, 'sheet4', 'm2:m101'); %write the second output set for r1
Appendix C: Identifying occupants

Objectives that are required to be achieved are identification of subjects and their positions while driving.

Recognition of different subjects that volunteered in the experiment is required using infrared imager. Eleven subjects are selected with somewhat different face features, height and hairstyles shown in Figure C-1. The aim is to distinguish between groups of subjects are ideally differentiate them individually.

![Figure C-1 Eleven volunteers visual images and interpolated thermal images](image)

For the ease of image processing and neural network analysis the tasks are divided into two main sections.
1. Subject identification and recognition

2. Position tracking and recognition of tasks being performed

The identification is based on the multiple temperature thresholding which is shown in (Amin et al., 2004). The face segmented image acquired is then used to take further measurements. An example is shown how the identification of volunteers is done. As seen from the Figure C-2 volunteers A, B and C all infrared images which are threshold as discussed in (Amin et al., 2004). A datum height is created anyone higher or lower than this height is placed in two different groups. It takes into account the height and inclination of the car seat. Also the volunteer is wearing glasses or not. As in the Figure C-2, Volunteer (B) is placed in above reference height group where as Volunteer (A) and (C) are in the below reference height group. Also Volunteer (A) and (B) are not wearing glasses, but volunteer (C) is wearing glasses. Thus similarly different groups are created that can distinguish between the eleven (11) volunteer of the experiments.

![Figure C-2 Volunteers A, B & C](image)
These parameters which measured are as follows:

1. above or below reference height
2. wearing glasses or not
3. median of Talley pressure monitor
4. head height and head width ratio (in pixels)
5. circularity of the thresholded image
6. particular features (in some cases)
7. filled area

As only three to four relations are enough to identify between a small group of volunteers during experiment. Many more quantitative features are created that can be measured and help to identify the individuals from the infrared images. Neural networks are used to differentiate between them.

Experiment 1: Neural Network for identification of subjects

Many back propagation neural network and radial basis neural network configurations are applied to identify the eleven volunteers in the infrared image. At the moment the infrared images features which are extracted using multiple thresholding technique is used as an input for the neural networks. For output the subjects are assigned identification numbers from one (1) to eleven (11).

Back propagation ANN results

The output results from the back propagation neural networks for identification of subjects are shown from Figure C-3 to Figure C-8:
Figure C-3 Back Propagation ANN with 'logsig' as transfer function and 1 layer

Figure C-4 Back Propagation ANN with 'tansig' as transfer function and 1 layer
Back propagation ANN (BPN) simulation results as shown in Figure C-5, Figure C-6. All three Back propagation neural networks are small and contain one (1) hidden layer. The input vector is 256 where as the optimized hidden layer neurons are found to be around 300 to 350 neurons. It can be seen that from Figure C-5 and Figure C-6 that 'logsig' and 'tansig' are much better transfer functions.

Further two (2) hidden layered ANN are created. The results from these back propagation neural networks are shown in Figure C-7 to Figure C-8.
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Back Propagation ANN, 2 Layer, 'logsig' transfer function

Figure C-6 Back propagation ANN with 'logsig' transfer function and two hidden layers

Back Propagation ANN, 2 Layer, 'tansig' transfer function

Figure C-7 Back propagation ANN with 'tansig' transfer function and 2 hidden layers
It can be seen from Figure C-6, Figure C-7 and Figure C-8, that 'logsig' transfer function performed much better in our circumstance. But as the complexity of the network and hidden layer increases there is not much influence on the result. Thus a simple single hidden layer neural network with 'logsig' transfer function is sufficient to achieve this result.

Radial Based ANN results

Six (6) radial based neural networks are created and simulated. The configuration of these six (6) neural networks is shown in Table C-1.
Intelligent Automotive Safety Systems: The Third Age Challenge

<table>
<thead>
<tr>
<th>Net</th>
<th>Target Goal</th>
<th>Spread</th>
<th>Spread</th>
</tr>
</thead>
<tbody>
<tr>
<td>Net1</td>
<td>0.0001</td>
<td></td>
<td>3</td>
</tr>
<tr>
<td>Net2</td>
<td>0.0001</td>
<td></td>
<td>2</td>
</tr>
<tr>
<td>Net3</td>
<td>0.0001</td>
<td></td>
<td>1</td>
</tr>
<tr>
<td>Net4</td>
<td>0.0001</td>
<td></td>
<td>0.75</td>
</tr>
<tr>
<td>Net5</td>
<td>0.0001</td>
<td></td>
<td>0.5</td>
</tr>
<tr>
<td>Net6</td>
<td>0.0001</td>
<td></td>
<td>0.25</td>
</tr>
</tbody>
</table>

Table C-1 Radial basis ANN Configuration

The simulation results from each network are shown in Figure C-9 to Figure C-14.

Figure C-9 Net1: Radial Basis ANN; Spread 3, Target Goal 0.0001
Figure C-10 Net2: Radial Basis ANN; Spread 2, Target Goal 0.0001

Figure C-11 Net3: Radial Basis ANN; Spread 1, Target Goal 0.0001
Figure C-12 Net4: Radial Basis ANN; Spread 0.75, Target Goal 0.0001

Figure C-13 Net5: Radial Basis ANN; Spread 0.5, Target Goal 0.0001
Figure C-14 Net6: Radial Basis ANN; Spread 0.25, Target Goal 0.0001

As the plots of simulation results shown in Figure C-9 to Figure C-14 the spread increases the results improve and when decreases the limit gets tighter.
ANN Conclusion for experiment 1

Back propagation takes longer time to train but a much simple back propagation neural network with only one hidden layer and ‘logsig’ transfer function and ‘linear’ transfer function as an output gives very similar result to that of high spread (around 3 or slightly higher) radial basis neural network. These two neural networks give higher accuracy than the rest of the neural networks tested on the thresholded infrared images.

To make these neural networks much more accurate a much intelligent approach of processing the infrared image should be done before feeding infrared images into the neural network. For example different features like height, pressure and white pixel count will achieve much accurate result.
Appendix D: Technical Data
IRI 1002 Online Thermal Imager Serial Protocol

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Quality Manager

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   5.1 Description of Calibration Sets 7
   5.2 Description of Startup Mode setting 7
   5.3 Advanced Commands Transmitted to Thermal Imager 8
   5.4 Advanced Commands Received from Thermal Imager 8
At power on, the Identity packet is automatically sent.

### 4.1 Basic Commands Transmitted to Thermal Imager

<table>
<thead>
<tr>
<th>Packet Type</th>
<th>Packet Size (Data)</th>
<th>Packet Name and Data Composition</th>
</tr>
</thead>
<tbody>
<tr>
<td>0xa0</td>
<td>No data</td>
<td>Stop imager</td>
</tr>
<tr>
<td>0xab</td>
<td>3 bytes</td>
<td>Send Temperature data (Multi-frame with resolution &quot;x&quot;)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• 1 byte - Resolution (1 = 1K, 10 = 0.1K)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• 1 byte - Number of Frames (0 = continuous, 1 to 255 no of frames)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• 1 byte - Frame Rate over N (1 - transmit every frame, ... 255 - every 255th frame, 0 = every 256th frame)</td>
</tr>
</tbody>
</table>

Table 1 Packet Data Definition – Basic Commands to Thermal Imager
### 4.2 Basic Commands Received from Thermal Imager

#### Packet Data contents

<table>
<thead>
<tr>
<th>Packet Type</th>
<th>Packet Size</th>
<th>Packet Name and Data Composition</th>
</tr>
</thead>
<tbody>
<tr>
<td>0x05</td>
<td>517 bytes</td>
<td><strong>Temperature data with temperature sensor value, (Res 1K)</strong></td>
</tr>
<tr>
<td></td>
<td></td>
<td>• 1 byte - Calibration Set used</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• 2 bytes - serial number: (only lower 2 bytes of serial number, see identity packet for full serial number).</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• 512 bytes = 256 values of 16 bit unsigned temperature data (Upper byte, Lower byte) in Kelvin. <strong>Resolution 1K</strong>.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• 2 byte temperature sensor value (UPPER BYTE - Integer temperature, LOWER BYTE - Fixed point fractional part of temperature).</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Lower byte (Bits 3 .. 0) contain unused status flags</td>
</tr>
<tr>
<td>0x06</td>
<td>517 bytes</td>
<td><strong>Temperature data with temperature sensor value, (Res 0.1K)</strong></td>
</tr>
<tr>
<td></td>
<td></td>
<td>• 1 byte - Calibration Set used</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• 2 bytes - serial number: (only lower 2 bytes of serial number, see identity packet for full serial number).</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• 512 bytes = 256 values of 16 bit unsigned temperature data (Upper byte, Lower byte) in Kelvin. <strong>Resolution 0.1K</strong>.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• 2 byte temperature sensor value (UPPER BYTE - Integer temperature, LOWER BYTE - Fixed point fractional part of temperature).</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Lower byte (Bits 3 .. 0) contain unused status flags</td>
</tr>
<tr>
<td>0x24</td>
<td>18 bytes</td>
<td><strong>Identity packet</strong></td>
</tr>
<tr>
<td></td>
<td></td>
<td>• 3 bytes serial number (High byte, middle byte, lowest byte)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• 2 bytes hex version number - Upper byte is the major version number, Lower byte is the minor version number, eg ver1.a2 = 0x01 0xa2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• 1 byte - specifies the number of calibration sets in the imager</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• 1 byte - indicates which calibration set it is using. (1 to n; where n is the number of calibration sets in the imager)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• 1 byte - Default serial resolution (only used by the imager if startup mode = continuous)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• 1 byte - Default frame rate over n (only used by the imager if startup mode = continuous)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• 1 byte = Default startup mode - Startup in silent mode or in continuous mode. (Silent = 0; Continuous = 1)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• 8 bytes = (Dummy chars reserved for future use).1 byte - specifies which calibration set to fetch the description from. (1 to n; where n is the number of calibration sets in the imager)</td>
</tr>
</tbody>
</table>

Table 2 Packet Data Definition – Basic Commands received from Thermal Imager

The temperature sensor reading in the data packet gives an indication of the temperature inside the imager enclosure.
Shortform guide to the IRI 1002 Online Thermal Imager Serial Protocol – Basic Commands

Hardware Specification
115200,8,n,1,no (115200 baud, 8 data bits, no parity, 1 stop bit, no handshaking)
RS 232 levels ← 12V

Example Packets

To the Thermal Imager

<table>
<thead>
<tr>
<th>Command</th>
<th>Packet Bytes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Send 1K Resolution, Single Frame, Full Rate</td>
<td>(10 bytes)</td>
</tr>
<tr>
<td>Decimal – 170,187,171,1,1,1,0,0,170,204</td>
<td></td>
</tr>
<tr>
<td>Hex – AA, BB, 0A, 01, 01, 00, 00, AA, CC</td>
<td></td>
</tr>
<tr>
<td>Send 0.1K Resolution, Single Frame, Full Rate</td>
<td>(10 bytes)</td>
</tr>
<tr>
<td>Decimal – 170,187,171,10,1,0,0,170,204</td>
<td></td>
</tr>
<tr>
<td>Hex – AA, BB, 0A, 01, 00, 00, AA, CC</td>
<td></td>
</tr>
<tr>
<td>Send 0.1K Resolution, Continuous Data, Every 8th frame (~ 1 per sec).</td>
<td>(10 bytes)</td>
</tr>
<tr>
<td>Decimal – 170,187,171,10,0,8,0,0,170,204</td>
<td></td>
</tr>
<tr>
<td>Hex – AA, BB, 0A, 00, 08, 00, AA, CC</td>
<td></td>
</tr>
</tbody>
</table>

From the Thermal Imager

<table>
<thead>
<tr>
<th>Command</th>
<th>Packet Bytes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temperature packet (0.1K resolution) with temperature sensor value, calibration set 1, serial number 129.</td>
<td>(525 bytes total packet size)</td>
</tr>
<tr>
<td>Decimal – 170,187,2,6,1,0,129,</td>
<td>(Packet preamble 7 bytes),</td>
</tr>
<tr>
<td>11,237 (upper byte, lower byte combined gives 3053 = 305.3K)</td>
<td></td>
</tr>
<tr>
<td>256 pixel values total = 512 bytes,</td>
<td></td>
</tr>
<tr>
<td>29,64 (temperature sensor value of 29.25; 2 bytes),</td>
<td></td>
</tr>
<tr>
<td>0,0,170,204 (Packet completion 4 bytes)</td>
<td></td>
</tr>
<tr>
<td>Hex – AA, BB, 02, 06, 01, 00, 11,</td>
<td>(Packet preamble 7 bytes),</td>
</tr>
<tr>
<td>0B, ED (upper, lower bytes combined gives 0BED = 3053d = 305.3K)</td>
<td></td>
</tr>
<tr>
<td>256 pixel values total = 512 bytes,</td>
<td></td>
</tr>
<tr>
<td>1D, 40 (temperature sensor value of 29.25),</td>
<td></td>
</tr>
<tr>
<td>00, 00, AA, CC (Packet completion 4 bytes)</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Command</th>
<th>Packet Bytes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temperature packet (1K resolution) with temperature sensor value, serial number 129.</td>
<td>(525 bytes total packet size)</td>
</tr>
<tr>
<td>Decimal – 170,187,2,5,1,0,129,</td>
<td>(Packet preamble 7 bytes),</td>
</tr>
<tr>
<td>1,49 (upper byte, lower byte combined gives 305 = 305K)</td>
<td></td>
</tr>
<tr>
<td>256 pixel values total = 512 bytes,</td>
<td></td>
</tr>
<tr>
<td>29,64 (temperature sensor value of 29.25; 2 bytes),</td>
<td></td>
</tr>
<tr>
<td>0,0,170,204 (Packet completion 4 bytes)</td>
<td></td>
</tr>
<tr>
<td>Hex – AA, BB, 02, 05, 01, 00, 11,</td>
<td>(Packet preamble 7 bytes),</td>
</tr>
<tr>
<td>01, 31 (upper byte, lower byte combined gives 0131 = 305d = 305K)</td>
<td></td>
</tr>
<tr>
<td>256 pixel values total = 512 bytes,</td>
<td></td>
</tr>
<tr>
<td>1D, 40 (temperature sensor value of 29.25),</td>
<td></td>
</tr>
<tr>
<td>00, 00, AA, CC (Packet completion 4 bytes)</td>
<td></td>
</tr>
</tbody>
</table>
5 Definition of Advanced Commands

In addition to the basic start and stop commands, the Thermal Imager also has some advanced commands that can be used to set the imager to various states.

List of commands

i. Request Identity Packet  
To Imager

ii. Request Number of Calibration Sets  
To Imager

iii. Request Calibration Set Description  
To Imager

iv. Use Specified Calibration Set  
To Imager

v. Set Startup Mode  
To Imager

List of received packets

i. Number of Calibration Sets in Imager  
From Imager

ii. Calibration Set Description  
From Imager

5.1 Description of Calibration Sets

The Thermal Imager can be calibrated with a number of temperature ranges. These options will have been specified at purchase of the unit. Each range has a “Calibration Set” associated with it. The Imager will be programmed with a default calibration set (temperature range). The user software can modify this through the serial interface. Each calibration set has a text description associated with it so that the user can decide which set is appropriate to use.

When a calibration set is used, the imager will automatically store this setting in non-volatile memory so that it will then be the default one used by the imager, even after a power down cycle. The non-volatile memory has a finite number of guaranteed write cycles (currently 100,000) after which, the default setting will not be stored correctly. However, the imager will continue to switch calibration sets correctly.

Applicable Commands: Request Number of Calibration Sets, Request Calibration Set Description, Number of Calibration Sets in imager, Calibration Set Description, Use Specified Calibration Set.

Suggested usage:
After power up during installation:

Request Number Of Calibration Sets;
Request Calibration Set Description for all calibration sets (1 to n)
Operator / installer to decide which one is best, send Use Specified Calibration Set command.
Request a single temperature packet and check “Calibration Set Used” byte is as expected.
(This setup is valid for that particular imager – serial number shown in Identity Packet.)

5.2 Description of Startup Mode setting

By default, the Thermal Imager will start up in “Silent” mode. However, the customer can set the Thermal Imager to startup automatically in “Continuous” mode when the imager powers up. This setting is stored in non-volatile memory and so is only required to be set at installation.

The options are the same as for the Temperature Packets: Serial Packet resolution 1K or 0.1K, FrameRateOverN and Startup Mode. The “Number Of Frames” command is not required as it will be outputting continuous frame data.

The imager will first output it’s Identity Packet before carrying out any startup mode requirements.

Applicable Commands: Set Startup Mode

5.3 Advanced Commands Transmitted to Thermal Imager
<table>
<thead>
<tr>
<th>Packet Type</th>
<th>Packet Size (Data)</th>
<th>Packet Data Composition</th>
</tr>
</thead>
<tbody>
<tr>
<td>0x96</td>
<td>No data</td>
<td>Request Identity packet</td>
</tr>
<tr>
<td>0x93</td>
<td>No data</td>
<td>Request Number of Calibration Sets</td>
</tr>
</tbody>
</table>
| 0x94        | 1 byte             | Request the description for a specified calibration set  
\[ 1 \text{ byte} \text{ - specifies which calibration set to fetch the description from. (1 to n; where n is the number of calibration sets in the imager)} \] |
| 0x95        | 1 byte             | Use Specified Calibration Set  
\[ 1 \text{ byte} \text{ - tells the imager which calibration set to use. (1 to n; where n is the number of calibration sets in the imager)} \] |
| 0x97        | 3 bytes            | Set Startup Mode  
\[ 1 \text{ byte} \text{ - specifies the default serial resolution 1 (1K), 10 (0.1K) (only used by the imager if startup mode = continuous)} \]  
\[ 1 \text{ byte} \text{ - specifies the default Framerate Over N. (0, or 1 to 255) (only used by the imager if startup mode = continuous)} \]  
\[ 1 \text{ byte} \text{ - Default startup mode - Startup in silent mode or in continuous mode. (Silent = 0; Continuous = 1)} \] |

Table 3 Packet Data Definition – Advanced Commands to Thermal Imager

5.4 Advanced Commands Received from Thermal Imager

<table>
<thead>
<tr>
<th>Packet Type</th>
<th>Packet Size (Data)</th>
<th>Packet Data Composition</th>
</tr>
</thead>
</table>
| 0x12        | 1 byte             | Number of calibration sets stored in the imager  
\[ 1 \text{ byte} \text{ - specifies the number of sets in the imager)} \] |
| 0x13        | 65 bytes           | Description for the specified calibration set  
\[ 1 \text{ byte} \text{ - specifies the set number (1 to n; where n is the number of calibration sets in the file. "0" means no set of that number)} \]  
\[ 64 \text{ bytes}; this is the description for the specified calibration set \] |

Table 4 Packet Data Definition – Advanced Commands to Thermal Imager
Appendix E: Publications
In-cabin occupant tracking using a low-cost infrared system

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Abstract - Vehicles in future will be safer and more intelligent, able to make appropriate and autonomous decisions to improve safety. From intelligent cruise control to intelligent airbag deployment conventional CCD cameras and computer vision are being used increasingly. Two major issues relating to the use of CCD cameras for the development of intelligent computer vision systems are the difficulty of human detection and invasion of privacy while driving. In this paper a low cost infrared system is proposed as a potentially practical solution for in-cabin monitoring of driver activities in an intelligent car.

I. INTRODUCTION

More than 3,500 people are killed and 35,000 seriously injured in cars annually in the United Kingdom [1]. Automobile safety is now an actively researched topic and one of the major concerns of the automobile industry, driven partly by increasingly strict regulations on vehicle safety. Mechatronic systems have become central to improving automobile safety on the road. Vehicle safety sensors may be broadly categorised according to location:
1. External vehicle safety sensors
2. In-cabin passenger safety sensors

Safety sensors mounted externally [2-7] include CCD cameras with image processing and stereoscopic vision, ultrasonic sensors to find distance and relative speed of obstructing objects, and FLRS (Forward looking radar sensors) to aid driver awareness of obstructing objects in conditions of low visibility, such as fog, night or heavy rain. Short range radar systems aid in reverse parking, obstruction detection and blind spot detection.

Internal sensors may be focused on the driver, and/or passengers, for in-cabin safety. The aim of this research is to develop a cost-effective and robust system of occupant tracking to enable the implementation of a variety of safety systems and strategies. In particular the use of thermal imaging for tracking occupant movements is being developed as part of a system to measure their ability of movement. This will help differentiate elderly, disabled or injured people. By identifying particular difficulties in movement it is proposed that measures may then be taken to make their journey safer and easier.

Many advanced safety systems will require knowledge of occupant position, movement and behaviour over time. For example intelligent air bags are being developed to deploy according to subject physique and position [7,9]. Position tracking is sometimes achieved by stereoscopic vision while others use single CCD cameras with image processing. However automatic tracking of occupants in-cabin using visual imaging encounters difficulties in distinguishing occupants from the background and from sensitivity to lighting variations, which in driving applications will inevitably be extreme. Another important consideration is the invasion of privacy associated with any continuous visual monitoring. Ultrasonic [8] and contact based sensors being developed to monitor occupant position [9-11] do not have this problem but are more limited in their potential for obtaining qualitative information.

It can be said that for in-cabin passenger tracking high spatial resolution infrared (IR) imagers can make human detection and tracking much easier, since they use emitted rather than reflected radiation. However the cost of the equipment becomes prohibitively high - a high spatial resolution infrared camera costs more than £9,000. The recent development of low-cost, low-resolution infrared cameras has reduced the cost problem and provides the ability to distinguish humans from backgrounds [12].

Low-resolution infrared thermographs [13, 14] and visual images [15] have been used successfully for human detection and other research. One advantage of using low-resolution visual and thermographic images is the speed of processing, making the system faster and cheaper. It has been shown that the computer does not require high resolution images in order to detect useful information from the image [15]. Another advantage of IR with regard to privacy is that position tracking can be done with no visual features or markings distinguishable on the image, making the system more socially acceptable.

The approach adopted is to use a low cost, low resolution IR camera which has recently become available at a cost of
less than one tenth of the normal higher resolution systems. The camera will be small enough, with some repackaging, to be mounted near the rear view mirror or on the "A" pillar with the driver's head and shoulders in view. The experiment described in this paper was carried out with the IR camera together with a CMOS webcam visual camera for comparative purposes. The procedure is shown in Figure 1.

Fig. 1 Overview of occupant tracking system

The work forms part of the early stages of a research programme to fully explore the potential capability and uses of low resolution thermal imaging for in-cabin occupant tracking and safety systems.

II. INFRARED THERMOGRAPHY

All objects continuously emit radiation at a rate and with a wavelength distribution that depends upon the temperature of the object and its spectral emissivity.

A black body is an object that absorbs all incident radiation and is a perfect radiator. The total radiation emitted by a black body is given by Stefan's Law, which states that "total radiation is (surface area) times (4th power of the temperature)'[16], mathematically expressed as:

\[ Q = \delta T^4 \]

Where \( \delta = 5.67 \times 10^{-8} \frac{W}{m^2 K} \) is the Stefan-Boltzman constant and T is the absolute temperature.

The energy emitted by a black body is the maximum theoretically possible for a given temperature. Objects that are not black bodies emit only a fraction of black body radiation. As the temperature increases the energy emitted at any wavelength increases and the wavelength of peak emission decreases. The thermal or infrared region contains a waveband from 2 to 15 micrometres. This electromagnetic spectrum range contains the maximum radiative emissions, which are used for thermal imaging purposes [17,18].

The infrared thermal imaging device is a different approach from other heat measuring devices, creating an image termed a thermogram which provides mapping of apparent temperatures. A black and white thermogram will relay spatial detail while a colour image reveals temperature differentiation. When looking at an object using the infrared imager the object is compared to a black body, an ideal radiator with an emittance of 1. Thermal imagers find heat transfer on the surface not beneath. An excellent example is that of the human face [19].

The infrared device used in this experiment is an IRISYS IR11001 thermal imager employing a 16x16 pyroelectric array, with a temperature range of -20°C to +90°C (+150°C with a reduced accuracy) [20]. The thermal imager views the scene with a rotating disc module and imaging optics, and communication is via RS-232 through an IBM-PC. The imager can capture up to eight frames per second. A germanium lens is used, instead of a regular glass lens, with a 20° field of view used in this case, thus from one metre the thermal imager has a viewable region of 0.352 metres square.

III. EXPERIMENTAL WORK

The experiment was conducted on a driving simulator with a number of drivers following the same sequence of driving activities. The CMOS visual camera had a resolution 288x288 pixels. Both cameras were mounted together: directly in front of the driver as a baseline trial to provide data for image processing and to assess the potential of the imaging system as a whole. The effects of camera position are being investigated as the next stage of the research.

A. Volunteer Selection

Eleven volunteers were selected on the basis of different height, build, hairstyle, face structure and spectacles.

B. Driving Simulator

A fully interactive driving simulator, the STI Driving Simulator by Systems Technology Inc, was used for the experiment. The STI Driving Simulator is very suitable for research purposes as it is one of the most stable driving simulation packages available, with 40 years of development. This simulator uses PC Microsoft® Windows based control and customised simulations can be created using a very basic script. The simulation is projected by a data projector onto a 4m by 3m screen and driven by the controls inside a Ford Scorpio car. The steering, brake, accelerator and speedometer
are connected to absolute encoders, which give analogue readings to the Data Acquisition Card (DAC). This DAC is connected and configured in the PC with an installed copy of the STI Driving simulator software.

The DAC takes 3 inputs in the form of analogue signals from steering wheel movement, brake pedal and accelerator. The projector simulation is also shown on the supervision PC that is used for autopilot mode, centring of steering with the screen and review of scenarios before running experiments. The simulation control PC delivers the main control of the simulation software and graphics. The encoder counts from the DAC are read directly from the STI Driving Simulator.

C. Scenarios
Scenarios for the STI driving simulator are created using a basic script language. In this experiment a single scenario was used, the duration of which ranged from 350 seconds to 500 seconds. The scenario starts from an urban area with a single lane and continues into heavy traffic, intersection crossings, traffic signals, pedestrians crossing the street, hills and bends. Further on the scenario develops into a long straight dual lane expressway until the session ends.

D. Sensors
For this experiment the IRISYS infrared imager and Webcam were mounted together on the driving simulator at a distance of one metre away from the subject. The Webcam provides an essential visualization tool for comparison and verification purposes during the image processing analysis.

E. Image Acquisition software
‘I-Quire’ software [21], developed by the author to perform the task of data acquisition for the thermal imager, and Video for Windows (VFW) supported the visual devices. The platform used for development is National Instruments LabWindows/CVI which has an ANSI C environment. This software can acquire up to 4 frames per second saving bmp and infrared data simultaneously. The duration of the image acquisition can be from 1 second to unlimited and can be paused during the acquisition.

The image frequency used in the experiment was 2 frames per second and image acquisition was done for the whole length of the simulation.

F. Experimentation

The experiment was conducted with an ambient temperature of 20 degrees and a trial run was undertaken by each volunteer before the start of the experiment. Around 800 visual images and thermograms were taken for each driver. During the experiment certain instructions were given to e.g. perform overtaking manoeuvres, slow down, look right and left at intersections and to simulate a crash situation by moving the head onto the steering wheel.
IV. IMAGE PROCESSING

The infrared images taken are analysed using MatLAB. These images are linearly interpolated from 16x16 pixels to 121x121 pixels. Interpolation does not add any extra information into the image but helps low-resolution infrared images to be visually analysed and gives a greater number of pixels to work on.

Four types of different temperature ranges are found in the images that can be thresholded. These are:
1. Background
2. Covered skin (with clothes or hair)
3. Face
4. Eyes, mouth and forehead.

Thresholded images for face separation are used further in the imaging tracking analysis. Facing forward is taken as a reference image from which motions are tracked. A comparison of driving task using visual and infrared thresholded image is shown Fig. 8.

![Infrared images and thresholded images](image)

Fig. 7 Multi thresholding of interpolated infrared images

Thresholded images for face separation are used further in the imaging tracking analysis. Facing forward is taken as a reference image from which motions are tracked. A comparison of driving task using visual and infrared thresholded image is shown Fig. 8.

![Comparison of different driving tasks](image)

Fig. 8 Comparison of different driving tasks of occupant using conventional camera and multiple thresholded infrared images

Software is written to plot the centroid of the face-segmented images. The software shows the plotted centroid with the last thresholded image. It can be seen from Fig. 9 that different regional classification is able to broadly classify the tasks of the driver.

![Plotting of centroid](image)

Fig. 9 Plotting of centroid from the thresholded images

Also it can be seen from Fig. 10 that the subject is wearing glasses. At the start of the journey the subjects put on a seatbelt, then drove mostly straight but encountering intersections, thus the centroids deviate to the left or right as the head turns.

Measurement of the subject’s head movement is by simple calculation as the field of view in infrared is 352 by 352 mm. It can be seen from Fig. 11 that the distance between the far left centroid and the centroid for looking forward, is 20 pixels. Thus by simple mathematics the furthest head movement is calculated to be 116 mm in the case shown below.

![Subject with glasses driving](image)

Fig. 10 Subject with glasses driving
Currently MatLAB is used for offline analysis as the system is in the experimental stages. The real time system will be implemented subsequently using National Instruments/CVI language due to the speed of data acquisition and image processing required.

V. RESULTS AND OBSERVATIONS

Experimental data from eleven volunteers, each containing 800 samples of infrared, was applied to the tracking algorithm. The thresholded infrared samples were then compared with visual data. Thus it can be said that in-cabin tracking using low-resolution infrared images has been achieved. The system can reliably locate the occupant with an accuracy of +/-15 mm.

Although the information received from the infrared sensor is two-dimensional it can give results comparable in accuracy with ultrasonic position sensors or contact based sensors, as the contact based sensors only track position based on seating position of the occupant. In comparison with visual image detection the infrared is far superior in detecting human motion within a wide range of conditions.

Use of low resolution thermal imaging for tracking occupant movements is now being developed as a key part of a multi-sensor system to measure drivers' capabilities and limitations of movement. Together with driving task analysis this will help differentiate elderly, disabled or injured people. By identifying limitations or difficulties of a particular person measures may be taken to make their journey safer and easier. A number of other potential applications and benefits of infrared imaging are also being identified as part of this work.

VI. ACKNOWLEDGMENTS

The authors gratefully acknowledge the contributions of A.F.Juna, F.Junejo and the participating volunteers.

VII. REFERENCES

EN.REFLIST
Abstract: Non-contact counting of people in a specified area has many applications for safety, security and commercial purposes. Visible sensors have inherent limitations for this task, being sensitive to variations in ambient lighting and colours in the scene. Infrared imaging can overcome many of these problems but normally hardware costs are prohibitively expensive. A system for counting people in a scene using a combination of low cost, low resolution visual and infrared cameras is presented in this paper. The aim of this research was to assess the potential accuracy and robustness of systems using low resolution images. This approach results in considerable savings on hardware costs, enabling the development of systems which may be implemented in a wide range of applications. The results of eighteen experiments show that the system can be accurate to within 3% over a wide range of lighting conditions.
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Automated people counting by using low-resolution infrared and visual cameras

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Abstract

Non-contact counting of people in a specified area has many applications for safety, security and commercial purposes. Visible sensors have inherent limitations for this task, being sensitive to variations in ambient lighting and colours in the scene. Infrared imaging can overcome many of these problems but normally hardware costs are prohibitively expensive. A system for counting people in a scene using a combination of low cost, low resolution visual and infrared cameras is presented in this paper. The aim of this research was to assess the potential accuracy and robustness of systems using low resolution images. This approach results in considerable savings on hardware costs, enabling the development of systems which may be implemented in a wide range of applications. The results of eighteen experiments show that the system can be accurate to within 3% over a wide range of lighting conditions.

Keywords: people-counting, imaging, infrared, artificial neural network (ANN)
Notation

$p$  Energy Radiated
$\lambda$  Wavelength
$T$  Temperature (Kelvin)
$h$  Planck's Constant
$c$  Velocity of light
$b$  Boltzmann Constant
$w$  Radiated energy
$\varepsilon$  Emissivity
$\eta$  Boltzmann constant

$P(q)$  Interpolated value
$L_i(q)$  Lagrange polynomial
$q$  Point at which interpolation takes place
$f_i$  Known values on the grid at points $(q_i)$

$t_i$  Desired or target response for $i$th unit
$y_i$  Actually produced response for $i$th unit
$E$  Error for a single training pattern in neural network
$\Omega$  Transfer function output value

$a_n$  Output thresholded image
$\alpha_n$  Thresholding value
$r$  Original image
$d$  Constant
$c$  Constant
$q$  Grayscale image

$x$  Infrared image
$\delta$  Average body heat
$m$  Thresholded infrared image
1. Introduction

Automated counting is an active research topic in many areas including biology [1], medicine, quality control and industrial machine vision processes amongst others. There are many situations where it is useful or essential to count people and numerous automated people-counting systems have been developed over the years. A variety of contact based sensors are in use, such as pedestrian barriers on entrances to public buildings and gateways. Most commercially available non-contact based counters use infrared beams or ultrasonic sensors, and specialized human information sensors are also developed for this task [2]. However the most commonly used non-contact system still remains the visual camera [3-5].

One present disadvantage with visual counting systems is the cost – a high spatial resolution visual camera and a frame grabber required for the system are still fairly expensive items. However a more fundamental problem, even with high spatial resolution cameras, remains the inaccuracy associated with visual detection of people. If a person is wearing the same shades of grey as the background it is difficult to distinguish between the background and the clothes. Also there are no reliable ways of distinguishing with accuracy a person from similar objects. These objects in the background are one of the main concerns, commonly raising false alarms in many automated people counting systems. Generally it can be said that background separation is not an easy task. Furthermore visual automated counting systems can only work in the presence of ambient lighting such as an office environment, sunlight, or other types of lighting. In case of emergencies, such as fire or blackouts, the system will malfunction during evacuation of the building and thus could be rendered useless at crucial times. Similar situations can occur with exterior use of visual people counters [5], there will be false alarms during night time if there is no special lighting arrangement in the area under consideration.

Thus a system is proposed to overcome these problems by using a low cost infrared thermal imager together with a visual camera. The visual camera uses an image-processing algorithm that can distinguish between people and objects with an accuracy of about 12%.
This system, developed by Schofield et al [4], uses visual automated counting but can be modified easily to accommodate low spatial resolution visual images. The working principle is based on the background training of visual images using a neural network.

2. Thermal Imaging

Thermal infrared (IR) imaging sensors respond to emitted, more than reflected, radiation. All objects emit heat by three means: conduction, convection and radiation.

Conduction transfers heat through solid objects; convection transfers heat through fluids; radiation transfers heat through electromagnetic radiation.

Objects continuously radiate heat with certain wavelengths, dependent upon the temperature of the radiating object and its spectral emissivity. As the object temperature increases the radiation increases. The radiation emitted includes the infrared emission which consists of electromagnetic wavelengths between 0.7 μm to 100 μm. Small ranges of infrared emission from the objects are detected by the thermal imager and then made visible as an image in the form of a thermogram – a mapping of apparent temperatures.

The concept behind infrared emission detection of the thermal imager is the assumption that a black body is a perfect radiator; it emits and absorbs all incident energy. The energy emission for the black body is the greatest possible for energy emission for that particular temperature. Radiation power emitted by a black body as given by Plank’s radiation law [6] is:

\[
p(\lambda, T) = \frac{2\pihc^2}{\lambda^2} \left[\exp\left(\frac{hc}{\lambda bT}\right) - 1\right]^{1/2} \tag{1}
\]

- \( p \) = Energy Radiated
- \( \lambda \) = Wavelength
- \( T \) = Temperature (Kelvin)
- \( h \) = Plank’s Constant
- \( c \) = Velocity of light
- \( b \) = Boltzman Constant
Real objects are not perfect emitters or absorbers. Thus emissivity ($\varepsilon$) of the real surface is defined as the ratio of thermal radiation emitted by a surface at given temperature to that of a black body for the same temperature, spectral and directional conditions [7, 8]. Thus the emissivity of a black body is 1 and all other real surface emissivities will be between 1 and 0.

According to the Stefan Boltzmann Law of emissivity radiation:

\[
\frac{w}{\varepsilon} = \eta \, T^4 \quad \left[2\right]
\]

- $w$ = Radiated energy
- $\varepsilon$ = emissivity
- $\eta$ = Boltzmann constant \(5.67 \times 10^{-8} \, \text{W m}^{-2} \text{K}^{-4}\)
- $T$ = Temperature (Kelvin)

Thermal imaging converts thermal radiation into a digital signal which is then converted into a visible image. This study uses a newly developed thermal imager of type IRYSIS IR1 1001. This offers many advantages including low cost, wide temperature measurement range and the capability to capture images on an IBM-PC via an RS-232C port.

The thermal imager is housed in an aluminium casing of 100 mm by 100 mm complete with optics, pyroelectric detector [9], chopping motor and optical modulator. It has a temperature measurement range of -20 to 90°C with an accuracy of +/-0.1°C [10]. Although it is a low resolution, 16 x 16 pixel, thermal imager it can be used to display images of up to 128x128 pixels using bilinear or bicubic interpolation. The interpolation process estimates values of intermediate components of continuous function in discrete samples. An interpolation technique does not add extra information into the image but can provide better thermal images for human perception. For bicubic interpolation, the output pixel value is the weighted average of the pixels in the nearest 4 x 4 neighbourhood. Mathematically, bicubic interpolation can be described as follows:

Let $L_i$ be a third degree polynomial. The Lagrange polynomial interpolation is given by [11]
\[ P(q) = \sum_{i=0}^{3} f_i L_i(q) \quad [3] \]

Where,

- \( q \): Point at which interpolation takes place
- \( P(q) \): Interpolated value
- \( f_i \): Known values on the grid at points \((q_i)\)
- \( L_i(q) \): Lagrange polynomial, for example

\[ L_i(q) = \prod_{k=0, k \neq i}^{3} \frac{(q-q_k)}{(q_i-q_k)} \]

Previous research \([4]\) has shown that low resolution visual images give similar visual information to that of high resolution devices, as the visual information will be processed by computer. A similar approach is used for low-resolution thermal images. A low resolution thermal imager will cost much less than a typical high resolution thermal imager, around one tenth of the cost, and will be much smaller than a conventional thermal imager. Additionally the low resolution imager is specially designed for embedded systems, where data can be directly streamed through an RS232 connection to the computer for on-line monitoring and off-line analysis.

3. Neural Networks

An artificial neural network (ANN) is an information-processing paradigm inspired by the way in which the densely interconnected, parallel structure of the human brain processes information. Neural networks resemble the human brain in the following two ways:

- A neural network acquires knowledge through learning.
- A neural network's knowledge is stored within inter-neuron connection strengths known as synaptic weights.

Artificial neural networks are collections of mathematical models that emulate some of the observed properties of biological nervous systems and draw on the analogies of adaptive biological learning. The key element of the ANN paradigm is the novel structure of the
information processing system. It is composed of a large number of highly interconnected processing elements that are analogous to neurons and are tied together with weighted connections that are analogous to synapses.

The main advantage of using a neural network is the full automation of the learning and classification processes, allowing them to be implemented in fully automated monitoring systems, such as people counting, to recognize and classify different patterns without human involvement. This eliminates any error or lapses associated with human concentration during a repetitive task.

Neural networks are composed of simple elements operating in parallel, inspired by biological nervous systems as mentioned previously. As in nature, the network function is determined largely by the connections between elements. Some Neural networks are classified as feed-forward while others are recurrent (i.e., implement feedback) depending on how data is processed through the network. Another way of classifying neural network types is by their method of learning or training, as some of the neural networks employ supervised training while others are referred to as unsupervised or self-organizing networks. The selection of supervised or unsupervised network is greatly dependent on the data to be processed for the training of the network.

During supervised learning of an ANN an input stimulus is applied that results in an output response. Then this response is compared with a desired output i.e. the target response. If the actual response differs from the target response, the neural network generates an error signal. A popular measure of the error ‘E’ for a single training pattern, is the sum of square differences i.e [12].

\[ E = \frac{1}{2} \sum_{i}(t_i - y_i)^2 \]  

where,
\[ t_i = \] desired or target response for ith unit,
\[ y_i = \] actually produced response for ith unit.
The error “E” is then used to calculate the adjustment that should be made to the network’s synaptic weights so that the actual output matches the target output.

In contrast to supervised learning the case of unsupervised learning does not require a teacher; i.e. no target output is required. It is usually found in the context of recurrent and competitive nets. In the case of unsupervised learning there is no separation of the training set into input and output pairs during the training session, the neural net receives as its input many different excitations, or input patterns, and it arbitrarily organizes the patterns into categories. When a stimulus is later applied the neural net provides an output response indicating the class to which the stimulus belongs. If a class cannot be found for the input stimulus, a new class is generated. However, it should be noted that even though unsupervised learning does not require a teacher, it requires guidelines to determine how it will form groups. Grouping may be based on shape, colour, or material consistency or on some other property of the object [12, 13].

3.1. The Backpropagation Neural Network

Backpropagation Neural Networks are one of the most commonly used neural network structures, as they are simple and effective, and have been used successfully for a wide variety of applications such as speech or voice recognition, image pattern recognition, medical diagnosis, and automatic controls. It is a supervised neural network, consisting of “n” numbers of neurons connected together to form an input layer, hidden layers and an output layer. The input and output layers serve as nodes to buffer input and output for the model and the hidden layer serves to provide a means for input relations to be represented in the output. Before any data has been run through the network, the weights for the nodes are randomly chosen, which makes the network very much like a newborn's brain, developed but without knowledge. When presented with an input pattern each input node takes the value of the corresponding attribute in the input pattern. These values are then “fired”, at which time each node in the hidden layer multiplies each attribute value by a weight and adds them together. If this is above the node’s threshold value, it fires a value of “1”; otherwise it fires a value of
"0". The same process is repeated in the output layer with the values from the hidden layer, and if the threshold value is exceeded, the input pattern is given the classification. Once a classification has been given it is compared to the actual, i.e. desired, classification and the error is fed back (backpropagated) to the neural network and used to adjust the weights such that the error decreases with each iteration and the neural model gets closer and closer to producing the desired output. This process is known as "training". The back propagation neural network used in this study uses a sigmoid function in the hidden layer and a linear function in the output layer [12]. Both functions can be expressed respectively as follows:

3.2. The RAM based Neural Network

Most conventional neural network training procedures, as mentioned above, are used to develop the required behaviour in a learning system, having assumed that the 'weight' parameters in which the system's knowledge is stored can be positive or negative and unboundedly large in size. These analogue weights, and the algorithms by which they are adapted, are not well suited to hardware implementation. However, in this study, a sequential (RAM based) neural network has been used which uses binary weights, i.e. 0/1 values, stored in RAM memory blocks which themselves play the role of the 'neurons' in the system. This approach, sometimes called 'weightless neural computing', has many advantages over other neural networks, such as fast network training. It uses 'one-shot' learning procedures very different from the iterative ones of conventional neural networks and furthermore they can operate well on low resolution images. In addition to this, in the case of RAM based neural networks, the bit-stream communication between RAM neurons, rather than being a hindrance to the system when learning, is actively beneficial in promoting generalisation. This refers to the neural network producing reasonable outputs for inputs not encountered during training (learning), whereas, other networks have to introduce such a 'blurring' of the input (so that in effect a wider range of patterns are seen during training) in a much more artificial way [14].
RAM based Neural Network Architecture:

As shown in Figure 5, the basic architecture is as follows:

- the input vector is divided into parts; each part is connected to the address inputs of a 1-Bit-RAM unit.
- The output of all the RAMs within one discriminator are summed. The number of discriminators needed in a network is determined by the number of classes which need to be distinguished by the network.

The 1-Bit-RAM unit, is a device which can store one bit of information for each input address. A control input is available to switch the mode of the RAM between 'Write' and 'Read' for learning and recall. Initially all memory units are set to '0'. During the learn ('Write') mode the memory is set to '1' for each supplied address; in the recall ('Read') mode the output is returned for each supplied address, either '1' (if the pattern was learned) or '0' (if the pattern was not learned).

The discriminator is the device which performs the generalization. It consists of several RAMs and one node which sums the outputs of the RAMs in recall mode. The discriminator is connected to the whole input vector; each RAM within the discriminator is connected to a part of this vector, so that each input bit is connected to exactly one RAM. The connections are preferably chosen by random.

4. Experimental work

The experiment was conducted by mounting the low-cost visual imaging device (Webcam) and the IRISYS IR11001 thermal imager looking vertically down. Markers are placed on the floor under consideration so that both infrared imager and visual camera are sharing the same information. The visual imager has a much wider field of view than the thermal imager, thus only a cropped visual view is taken into consideration.

Special software was developed using National Instruments LabWindows/CVI [15]. This software communicates with the visual imager using a USB 1.1 interface and the infrared imager using RS-232C. The data is stored offline for further analysis. The software is flexible
enough to store at different frame rates and different resolutions, and also displays the data which is being stored.

The resolution selected for VGA is 320x240 pixels while infrared resolution is fixed at 16x16 pixels. The images are taken at 4 frames per second (FPS), even though the infrared imager is capable of up to 8FPS, as here analysis is based mostly on individual images rather than time-based imaging analysis.

Three control experiment scenarios were used. Each scenario was based on six experiments with differences in position, movement of subjects and different lighting conditions. The background images with no subjects were also taken each time. Each experiment conducted contained around 150 visual and infrared samples of data stored on a hard disk. The length of each experiment varied from 3 to 5 minutes depending upon the subjects involved, and during all experiments the data acquisition software was kept running. The three scenarios were as follows:

4.1. Elevator camera (static)

In this scenario ten volunteers were involved which resulted in thirty tests. This simulates the elevator surveillance camera with a restriction of any volunteer leaving the scene during the length of each test. During each test volunteers are asked to stand for five seconds at random positions in the area which is being monitored. Also the number of volunteers increased as the test progressed. The maximum number of volunteers in tests was five and each test was repeated five times with random selection of volunteers.

4.2. Gate Camera

This scenario simulates the gate camera for counting. Volunteers were asked to enter the scene from one side and leave on the opposite side. Thirty tests were conducted, with each test repeated five times with a random selection of volunteers. Two special conditions, i.e. one
person standing within the gate for a certain period of time and one person stopping and returning to where he/she entered from, were included in these tests.

4.3. Elevator camera (dynamic)

This scenario simulates the actual elevator surveillance camera. The volunteers in this scenario are allowed to leave and enter the scene but only from one side which is the elevator door. The maximum number of volunteers in tests was ten. During the test volunteers were given specific instructions when to enter or leave the scene. It also simulates the peak timing as well as off-peak timing during the day. As in the previous scenarios all volunteers were selected randomly for each test to maintain the validity of the final result.

5. Image processing strategy

The visual system used is lower cost than traditional CCTV cameras, around $1/10^6$ of the cost. The low cost CMOS sensor used by the visual system also develops a noise factor, which presents a major issue to be considered during the visual analysis. Thus images with simple subtraction with respect to the reference scene do not provide a consistent image in our case which can be thresholded.

The visual analysis carried out is very similar to that done by Schofield et al [4] except that the equipment used is low cost. The thermal imaging analysis is also done separately. The results of each analysis are then further compared to increase the accuracy of the system. These showed that the system can be developed to be capable of counting in a smoked filled room and other emergency situations, which is not the case with conventional visual counting systems. In the following sections both visual and infrared data are analysed separately and then the combined results are discussed.

5.1. Visual Analysis

The visual analysis uses the background identification technique employed by Schofield et al [4]. This system avoids any standard approach which fails to take light variations into
account, hence it is independent of light intensities in the image. Thus this process is chosen for visual analysis for the development of our system with some modifications, for example we do not require location information in an image as it is not necessary in the proposed application. The visual counting system developed should have the following characteristics:

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Requirements</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy</td>
<td>Approximately 10%</td>
</tr>
<tr>
<td>Error</td>
<td>Maximum of +/-1 error in 4 to 10 people in a scene</td>
</tr>
<tr>
<td>Lighting conditions</td>
<td>Adaptable to any indoor lighting conditions</td>
</tr>
<tr>
<td>Adaptability</td>
<td>Most scenes in indoors buildings</td>
</tr>
</tbody>
</table>

Table 1. Design guidelines for visual counting system

5.1.1. Stage 1a: Pre-Processing

The pre-processing stage for visual analysis consists of resizing and thresholding. The initial image acquired from the experiment is 288x288 pixels. This is then reduced to 72x72 pixels. The reduction in resolution allows faster processing and a faster counting rate with negligible degradation in the thresholding result. For example, for the initial image of 288x288 pixels thresholding takes about 4.5 seconds using a fast processing speed while 72x72 pixels takes only about 2.5 seconds using MatLAB. This will improve significantly after final development of the system using a programming language such as C or C++.

Following resizing a reference image from each experiment is taken. Reference images are merely background images with no people in the scene. These reference images are thresholded not by the constant greyscale value but by applying adaptive local thresholding. The neighbouring pixel will allow the intensity of pixels to be compared with each other. If the comparison of these pixels is high, up to a certain value set by another variable \( \alpha_n \), the pixel is turned black otherwise white. Thus it can be mathematically expressed as:
Where

\[ a_{th} = \begin{cases} 1 & \text{if } \alpha_h > \left| r_{(i,j)} - r_{(i-1,j-1)} \right| \\ 0 & \text{if } \alpha_h \leq \left| r_{(i,j)} - r_{(i-1,j-1)} \right| \end{cases} \]

[5]

\( \alpha_h = \) Thresholding value

\( r = \) original image

\( o_h = \) output thresholded image

\( i = 1 \) to 72

\( j = 1 \) to 72

Here ' \( \alpha_{th} \)' is the global thresholding value of the image being processed. To calculate this value 1/3rd pixel values of images are randomly selected. The difference of intensities of these pixels is taken from their diagonal neighbour. Here two constants 'c' and 'd' are introduced in the thresholding value of ' \( \alpha_{th} \)'. After summing all of the intensity difference values the final value is multiplied by a constant 'c', which is less than 1. The value acquired is then added to the constant value of 'd'. The thresholding expression is mathematically expressed as:

\[ \alpha_{th} = d + c \sum_{k=1}^{72} \sum_{l=1}^{72} \left| q_{(k,l)} - q_{(k-1,l-1)} \right| \]

[6]

Where

\( \alpha_{th} = \) Thresholding value

\( d = \) Constant

\( c = \) Constant

\( q = \) Grayscale image

\( k = 1 \) to 72 (random values)

\( l = 1 \) to 72 (random values)

The optimal values of 'c' and 'd' are found by experimenting with the visual images taken during the experiment.
5.1.2. Stage 2a: Background Identification

The background identification is based on the RAM based neural network creation and training of that network. Only background images are trained using this network.

The thresholded image is divided into 4x4-sections, with 18 sections in each row and 324 altogether in the 72x72 pixel image. We consider each 4x4-section containing 16 pixels divided further into four sections, which are termed sub-sections. These sub-sections, containing four pixels each, are then randomly selected, and this selection remains the same over the life of a neural network. These randomly selected sub-sections are used as the addresses of RAM. For each 4x4 section created and randomly selected 4 sub-sections create a single classifier.

Training of a RAM based network is done by reading the 4 pixels from each group in 4x4 section outputs 1 to the RAM of that certain address as shown in Figure 5. For example if the value of the 4 randomly selected pixels is 0101 then it outputs 1 to the corresponding memory output of that address. Then it starts summing up all values in the memory addresses, which are specific for each individual 4 pixel group. Thus for every section of the image seen it outputs 1 into the RAM of that section address. It goes on until all the background samples are trained for that network. There is no reason to run the samples again through the network for a background already seen, as the result will always be the same for that particular image.

To simulate the image using a trained network a thresholded sample of the image is fed into the network. The sample image is then divided into the random sections, which are the same as that of the trained network. The addresses of sample images are compared with the trained network values. If the network has already seen the same section during training it outputs '1', if the network hasn’t seen anything like the section it outputs ‘0’. An output image is constructed with 1’s as the background and 0’s as the unseen object during the training. After inverting the image the unseen objects or people then appear as a cluster of 1’s in that image.

51 reference samples are used for training of the RAM-based neural network.
A 5x5 section is scanned over the output image by the neural network. For highest counts found in 5x5 sections in the image a count is incremented, and the 3x3 section in the middle is set to zero whereas the 16 outside values are halved. This process is continued until a certain cut-off value is achieved for the image. An optimized cut-off value is found by comparing the result found with the actual result.

5.2. Infrared Analysis

For the development of the low-resolution infrared counting system certain guidelines were laid down as follows:

<table>
<thead>
<tr>
<th>The infrared analysis system developed will be used in conjunction with the visual system but can be used as a stand-alone system with very slight modifications.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Accuracy</strong></td>
</tr>
<tr>
<td><strong>Error</strong></td>
</tr>
<tr>
<td><strong>Adaptability</strong></td>
</tr>
<tr>
<td><strong>Lighting Variations</strong></td>
</tr>
</tbody>
</table>

Table 2. Design guidelines for Infrared Counting system

5.2.1. Stage 1b: Pre-processing

Infrared data taken from the experiment are taken offline into MATLAB. The raw infrared data taken from the experiment is interpolated to find the 'average body heat'. The temperature of a person is generally higher than the background, except in very hot
areas such as desert, but as this experiment is conducted inside a building we can assume a reasonably consistent temperature difference. Average heat of the background image in this experiment is found to be:

\[
\text{average heat} = \frac{\sum \text{pixels}}{256} \approx 24.3^\circ \text{Celsius}
\]

The internal temperature of the IRISYS® infrared camera remains 32.375 °Celsius. Thus the overall temperature ranges for the duration of our experiment remain within:

- \( \min \text{body temp} = 27^\circ \text{C} \)
- \( \max \text{body temp} = 32^\circ \text{C} \)
- \( \delta = 29.5^\circ \text{Celsius} \)

where
- \( \delta = \text{Average body heat} \)

The 'average body heat' calculated from the infrared data is then used as the thresholding value for the experiments conducted. This 'average body heat' varies upon weather conditions and location of the experiment, such as whether it is conducted indoors or outdoors.

Infrared images of 16x16 pixels are processed using the following equation:

\[
[m](j,k) = \begin{cases} 
1 & \text{if } x \geq \delta \\
0 & \text{if } x < \delta 
\end{cases}
\]

where
- \( x = \text{Infrared image} \)
- \( \delta = \text{Average body heat} \)
- \( j = 16; \)
- \( k = 16; \)

Let \( x \) be an element of the original matrix of 16x16 elements from the infrared imager, \( m \) is an element of the thresholded matrix and \( \delta \) is the average body heat.
The infrared images after thresholding at average body heat give a distinguishable result that can be used for object recognition. But this is true only for small numbers of people as when the area under consideration becomes crowded then the algorithm becomes unreliable and hence further processing is necessary.

5.2.2. Stage 2b: Back Propagation Neural Network

For infrared image counting neural network areas are selected as the images are small, up to 16x16 pixels. After thresholding the infrared images are trained on back propagation neural networks.

A back propagation neural network is created. The specification for the final network selected is as follows:

<table>
<thead>
<tr>
<th>Inputs</th>
<th>256</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hidden Layer</td>
<td>1</td>
</tr>
<tr>
<td>Hidden Layer Neurons</td>
<td>280</td>
</tr>
<tr>
<td>Hidden Layer Function</td>
<td>Sigmoid Function</td>
</tr>
<tr>
<td>Output Layer Neurons</td>
<td>1</td>
</tr>
<tr>
<td>Output Layer Function</td>
<td>PureLin Function</td>
</tr>
<tr>
<td>Training Performance goal achieved</td>
<td>0.00642496</td>
</tr>
<tr>
<td>Epochs</td>
<td>500</td>
</tr>
<tr>
<td>Learning rate</td>
<td>0.005</td>
</tr>
<tr>
<td>Training Samples</td>
<td>360</td>
</tr>
</tbody>
</table>

Table 3. Configuration of optimized neural network for Infrared Analysis
Training of the backpropagation neural network is done by using twenty (20) samples from all eighteen (18) experiments as fed into the network.

6. Results

6.1.1. Infrared neural network simulation and results

The results acquired from the infrared data are plotted in the form of percentage error, with the error plot based on the simulation of 200 samples selected from each of 18 experiments. The error tends to increase as the number of people counted in the scene increases though there is much scatter and the error does not continue to rise as the numbers approach the maximum of ten.

6.1.2. Visual RAM based neural network simulation and result

As for visual images, the system is within 5% for less than six people in each scene. But as the actual number of people in each scene increases the error percentage increases to around 12%. This is due to people standing very close to each other, as would be the case for example at peak time in elevators. To overcome this error in the system infrared and visual results are combined.

6.1.3. Combined results of visual and infrared systems

It can be seen from the above results that an infrared system is capable of predicting a high density of people with high accuracy, whereas a visual system has proved to be more reliable for predicting lower densities of people. Therefore, in order to optimize the overall accuracy of the system, fusion of results from thermal and visual systems is carried out by taking percentage error and shifting the weight of results with less error percentage. As a result, as shown in Figure 9, the maximum percentage error has been reduced to 3%, even for scenarios containing a high density of people.
Conclusions

Combining two automated counting systems, visual and infrared, has been shown to give significant improvements in accuracy. The percentage error of 3% is far more accurate than either the visual RAM based system alone. This percentage error remains at 3% for more than six people in the experiment with both visual and infrared sensing. This was not the case with the visual counting system working without the infrared camera. The low resolution, low cost infrared imager can provide slightly less accurate but very reliable counting in low or zero light conditions, making it suitable for emergency situations.

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\[ \Omega(n) = \frac{1}{1+e^{-n}} \]

Linear Function

\[ \Omega(n_1) = \alpha n_1 \]

where \( \alpha = 1 \)

Sigmoid Function
Stage 1a: Pre-processing
- Resize
- Thresholding

Stage 2a: Background Identification
- Divide into sections
- RAM Network creation
- Training

Stage 3a: Object count
- Locate object
- Get count

Stage 1b: Pre-processing
- Thresholding
- Reshape

Stage 2b: Count
- B.P. Network creation
- Training

Stage 3b: Object count
- Network Result Count

Stage 4: Comparison
- Result Comparison
- Optimized Count
Visual Image  Thresholded Image
Randomly selected 4 sections
Figure(s) 6

Click here to download high resolution image

16x16 pixel infrared image

Threshold
Reshape

256 Inputs

280 neuron hidden layer
Sigmoid Function

1 neuron output layer
Purkin Function
Figure(s): fig7

Click here to download high resolution image

Percentage error Vs Actual Count

<table>
<thead>
<tr>
<th>Percentage error</th>
<th>0.5</th>
<th>1</th>
<th>1.5</th>
<th>2</th>
<th>2.5</th>
<th>3</th>
<th>3.5</th>
<th>4</th>
<th>4.5</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual number of people</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
<td>8</td>
<td>9</td>
</tr>
</tbody>
</table>
Combined percentage error of visual and infrared

Percent error of visual and infrared people count

Actual number of people
Driver tracking and posture detection using
low resolution infrared sensing

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Abstract

Intelligent sensors are playing an ever-increasing role in automotive safety. This paper describes the development of a low-resolution infrared (IR) imaging system to continually track and identify driver postures and movements. The resolution of the imager is unusually low at 16 by 16 pixels. An image processing technique has been developed using neural networks operating on a segmented thermographic image to categorise driver postures. The system is able to reliably identify 18 different driver positions and results have been verified experimentally with 20 subjects driving in a car simulator. IR imaging offers several advantages over visual sensors; it will operate in any lighting conditions and is less intrusive in terms of the privacy of the occupants. Hardware costs for the low-resolution sensor are an order of magnitude lower than conventional IR imaging systems. The system has been shown to have the potential to play a significant role in future intelligent safety systems.

Keywords: Infrared sensing, Artificial Neural Network (ANN), machine vision, intelligent safety system
1 INTRODUCTION

This paper discusses research into safety systems based on the use of a low-resolution infrared sensor for driver posture detection and position tracking. The ability to detect driver position and movement will be a key enabling factor in the development of a number of current and future safety systems. These may range from detecting out-of-position (OOP) occupants for safe airbag deployment to time-based monitoring of behaviour, for example to detect periods with attention away from the road or evidence of drowsiness.

This research has initially been focused on the needs and problems of older, or 'third-age', drivers. Transportation by private car is an important factor for the independence and quality of life of many older people. Demographic changes and reductions in birth rate have resulted in a large increase in the ageing population of industrialised countries. At present one third of the population in these nations is over 55 [1, 2] and, with the average age rising, the number of older drivers will continue to increase for the foreseeable future. The deterioration of driving abilities with advancing age is therefore a cause for concern [3]. Deterioration of cognitive, physical and visual abilities leads to increasing risks for older people [4], although these are mitigated to some extent by fewer and shorter journeys and a tendency to avoid night driving.

The term 'third-age' is generally applied to those over 55, although this definition is not universally accepted [3, 5]. The adage 'you are as old as you feel' holds true and people in their 60's and 70's may be more active than some younger people. However it is clear that, as the 'grey' population increases, the needs of the over 55's will have a greater impact on the design of many products in the future.

Problems encountered by third-age drivers typically include reading traffic signs and signals, observing road markings, reading the instrument panel, changing lanes or
merging in high speed traffic, turning the head whilst parking or reversing, making U-turns and turning at crossroads or T-junctions. Many tasks that involve neck and trunk movements are restricted in older people [6]. Cars must be designed for use by the full spectrum of the adult population. The subject of automotive ergonomics and safety is clearly complex and a detailed discussion of older drivers’ problems and characteristics is beyond the scope of this paper.

It is reasonable to assume that many of the difficulties and risks typically encountered by this older group will also apply to other groups, of any age, whose driving may be affected by physical impairments. The aim of the research described in this paper is to provide the basis for a system which, ultimately, will make driving safer and more pleasant for any impaired, as well as able-bodied, driver.

Additionally the system may be of benefit to Ergonomists, since observing and analysing driver postures and movements can be difficult and time-consuming. Many current procedures involve marker-based visual systems and others use load cells or pressure mats installed in the car seat [7, 8], methods which are not entirely practical for use in real-time in a real car environment. Load cells and pressure mats are not practical to use in the experiment because if the driver had a wallet in his back pockets it would create false readings other factors are limited availability and high cost. The IR system may provide a convenient and effective ergonomics tool for driver movement and behaviour analysis.

Infra-red (IR) imaging offers the ability to work in any ambient lighting conditions, a major advantage over visual cameras. The IR sensor used throughout this research programme is an IRISYS IRI1002 thermal imager with a resolution of 16 by 16 pixels. The advantages offered by this particular sensor include the relatively low cost when compared with high resolution IR cameras (hundreds rather than many thousands of
pounds) and the small size. Also, importantly, the low resolution protects the privacy of the car occupants as only indistinct images composed of areas of colour or grey levels are obtained.

2 INFRARED THERMOGRAPHY

An infrared imager measures infrared radiation emitted by objects - light with a wavelength in the range of 0.78 to 100 μm. This particular range is unseen by the naked human eye, however infrared imagers with different specifications can capture particular ranges of infrared wavelengths.

The principle behind infrared emission detection is based on the assumption that the black body is a perfect radiator, emitting and absorbing all energy that is incident on it. The energy emitted by a black body is the highest possible energy emission for that particular temperature. As real objects are not perfect black bodies, i.e. a perfect absorber or emitter, the emissivity of the real surface is the ratio of the thermal energy emission from the surface to that of a black body at the same condition as that of the real body [9,10].

The infrared imager used in this paper is a long wavelength infrared imager (LWIR), also termed a far infrared imager. It can measure infrared radiation from 8 to 24 μm wavelength and has a low resolution of 16x16 pixels. This low resolution device is approximately one tenth of the cost of a conventional infrared imager, allowing infrared imaging to be considered in areas other than military and defence usage.
3 IMAGING ALGORITHM

3.1 Methodology

In this study a driver posture tracking system is developed. The tracking algorithm has three stages of processing as shown in Figure 1. The processing stage makes use of artificial neural networks (ANN). The detected posture is converted into a code-based description of the driver's position after processing, referred to as a 'p-code'. The data comes from the low resolution infrared imager installed inside a car at a suitable location and, in this study, the thermographs from the infrared imager were taken for offline analysis. Experiments were conducted in a STISIM® car simulator to verify the algorithm developed.

3.2 Pre processing

Data Acquisition software

The bespoke data acquisition software used was developed by the authors for both the infrared and visual image acquisition using National Instruments LabWindows/CVI. The user interface is shown in Figure 2. This software acquires webcam images and thermographs in software based real-time. The image acquisition frequency in the experiment was set at 2 frames per second (FPS), selected on the basis of the length of experiment. Image acquisition was done for the whole length of the simulation scenario. File naming and storing is structured as a vast amount of data must be stored during each experimental run, therefore batch renaming and storing data in folder options are included. The DAT file generated by the data acquisition software is read in MatLAB using a function written by the author.
Infrared Interpolation

The interpolation process estimates values of intermediate components of a continuous function in discrete samples. Interpolation is extensively used in image processing to increase or decrease the image size. An interpolation technique does not add extra information into the image but provides a better image for human perception. In this case interpolation simply provides a larger thermograph area to work on, as a 16 x 16 pixel image, as shown in Figure 3, does not provide sufficient visual information. There are commonly five types of interpolation used: cubic, spline, nearest, linear and hyper-surface [11]. The cubic and spline interpolation are superior to other interpolated functions but due to computation complexities, and time taken by the spline interpolation, linear interpolation is preferred, as it is the simplest type of interpolation and is faster as less computation is required. No significant advantage would have been gained by using one of the other methods. A single infrared image is shown in Figure 3 with four types of interpolation in greyscale.

3.3 Processing

Segmentation

The devised adaptive segmentation method is based on the IR histogram. This method will compensate for slight temperature changes. The histogram of thermographs taken from the experiment contains two peaks on each extreme (Figure 4). The peak with the lower intensity values (black) represents the background and the peak with the higher intensity values (white) represents the subject.
Region allocation

After interpolation and segmentation of the infrared thermograph it is divided into three regions, based upon the field of view and the position of the driver, as shown in Figure 5. The full image size is 121 x 121 pixels.

Splitting of the IR image into three regions is a novel approach used as the basis for an algorithm which is designed to maximise the information gained from the limited resolution thermograph. The three regions are associated with different parts of the driver’s body and generally indicate different types of activity. These regions are labelled as ‘Torso region R1’, ‘Head region R2’ and ‘Arm and shoulder region R3’.

With the infrared imager one metre away mounted on the front left (passenger side) ‘A’ pillar of the car the field of view is 355mm square approximately.

‘Torso region R1’ is termed as such because any activity in this region necessitates trunk movement, and therefore it becomes the focus when the driver is leaning or looking down. This part of the infrared image is about 180mm by 200mm in size, or 61 pixels by 80 pixels. The ‘Head region R2’ focuses on head movements and is the most critical area. Its size in the infrared image is again 180mm by 200mm divided into 61 pixels by 80 pixels. The ‘Arm and shoulder region R3’ looks for arm and shoulder movements with respect to the steering wheel. This is the region where most movements are recorded, whenever the driver changes posture or moves the steering wheel. The location of region R3 is the lower part of the infrared image with a 150mm by 355mm field of view, containing 121 pixels by 41 pixels.

P-code description

For neural network results to be easily readable a numerical value for each region is allocated which points to a particular type of posture. These values are then looked up in Table 1 to identify a unique letter code, or ‘p-code’, which describes the body position in each region.
Table 1. Posture codes

<table>
<thead>
<tr>
<th>Region</th>
<th>ANN Numerical output</th>
<th>Posture description</th>
<th>P-code</th>
</tr>
</thead>
<tbody>
<tr>
<td>R1</td>
<td>1</td>
<td>Upright posture</td>
<td>N</td>
</tr>
<tr>
<td>R1</td>
<td>2</td>
<td>Leaning forward</td>
<td>E</td>
</tr>
<tr>
<td>R1</td>
<td>3</td>
<td>Looking Down</td>
<td>D</td>
</tr>
<tr>
<td>R2</td>
<td>1</td>
<td>Looking Ahead</td>
<td>F</td>
</tr>
<tr>
<td>R2</td>
<td>2</td>
<td>Looking Left</td>
<td>L</td>
</tr>
<tr>
<td>R2</td>
<td>3</td>
<td>Looking Right</td>
<td>R</td>
</tr>
<tr>
<td>R3</td>
<td>1</td>
<td>Hands on Steering</td>
<td>S</td>
</tr>
<tr>
<td>R3</td>
<td>2</td>
<td>Hands not on Steering</td>
<td>NS</td>
</tr>
</tbody>
</table>

All three region codes are then combined to describe a particular posture. For example N-R-S indicates an upright position and looking right with hands on the steering wheel, typical of a posture adopted when entering a roundabout or at a ‘T’ junction (see the later comparison with real video data). In comparison D-L-NS would indicate a driver looking down to the left side with hands not visible on the steering wheel, which means that the driver might be putting on a seat belt or accessing a dashboard compartment and therefore, if the movement is any more than momentary, the car should not be in a moving state.

Feature extraction

Selection of features from the image is a vital step to enable the imaging algorithm to give useful and accurate results. Therefore a great deal of care needs to be taken in
feature selection and a procedure has been devised to find each appropriate feature for neural network input, see Figure 6.

Each of the three regions of the IR image is dealt with separately as far as feature selection and recognition is concerned. The three categories of posture that will be defined in the neural network are non-leaning postures, leaning postures and looking down postures. 'Head region – R2' is considered the most critical. The three main movements identified in this region are looking ahead, i.e. normal driving, looking right and looking left. In the 'Shoulder and arm region – R3' two positions are identified for training the neural network, these are hands-on and hands-off the steering wheel.

In region – R2, the first posture, i.e. "looking ahead", numerous thermograph samples are taken for each volunteer. Similar samples are also obtained for two other postures, i.e. looking left and looking right. Two imaging features, i.e. angle and area, from the above mentioned thermograph images are used to distinguish between three postures.

**Neural network construction and training**

The neural network for each region is separate, hence there are three neural networks working simultaneously on a single thermograph. Furthermore for the purpose of comparing the types of neural network for each region three different types of neural network are constructed. These are multi-layered perceptron, radial basis network and a self-organized map network. Comparison and evaluation of all three networks results in determining the best neural network for that particular region. These three types are selected because each has good ability to differentiate between different parameters [12].

Training data is selected to cover all types of motion and the frequency of motion. Three hundred training samples for each region are taken, i.e. one hundred samples
for each different output. All types of network constructed for each region and for each subject contain a common set of input data and a simulation set three times larger to verify the results i.e. nine hundred simulation samples in all. The construction of all nine neural networks is shown in Table 2.

<table>
<thead>
<tr>
<th>Torso region ‘R1’</th>
<th>Head region ‘R2’</th>
<th>Arm and shoulder region ‘R3’</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inputs</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(area R1)</td>
<td>(area/angle R2 &amp; area R2)</td>
<td>(area R3)</td>
</tr>
<tr>
<td>MLP Layers 2, Neurons 2</td>
<td>Layers 2, Neurons 5</td>
<td>Layers 2, Neurons 5</td>
</tr>
<tr>
<td>Multi layer perceptron</td>
<td>Inner Layer: Sigmoid function</td>
<td>Inner Layer: Sigmoid function</td>
</tr>
<tr>
<td></td>
<td>Output Layer: Linear function</td>
<td>Output Layer: Linear function</td>
</tr>
<tr>
<td></td>
<td>Goal: 0.001</td>
<td>Goal: 0.001</td>
</tr>
<tr>
<td>RBN Spread constant: 1</td>
<td>Spread constant: 1</td>
<td>Spread constant: 1</td>
</tr>
<tr>
<td>Radial basis network</td>
<td>Inner Layer: Radial function</td>
<td>Inner Layer: Radial function</td>
</tr>
<tr>
<td></td>
<td>Output Layer: Linear function</td>
<td>Output Layer: Linear function</td>
</tr>
<tr>
<td>SOM Goal: 0, Epochs: 25</td>
<td>Goal: 0, Epochs: 25</td>
<td>Goal: 0, Epochs: 25</td>
</tr>
<tr>
<td>Self organizing map</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2. Neural Network construction specifications
4 EXPERIMENTATION

The objective of the experiment was to acquire representative information from the infrared imager to test and validate the driver posture tracking methodology.

The conditions in the experiments were arranged to be as close as possible to that of driving a real car. Driving simulator scenarios were developed to enable subjects to interact and drive as realistically as possible.

Driving volunteers

20 subjects were studied during this experiment with 10 male and 10 female drivers, with ages ranging from 17 to 65 years old. All subjects had driving experience, with the older drivers having the most experience.

IRISYS Imager: Serial Protocol programming

The IRISYS IRI1002 thermal imager has its own protocol which needed to be converted into an infrared image. The software has to be compatible with hardware specifications for the thermal imager, i.e. 1,15,200 baud, 8 data bits, no parity, 1 stop bit and no handshaking.

Infrared acquisition software

Infrared acquisition software, developed by the author, was used in this experiment and has also previously been used by Amin et al [13, 14]. This software acquires webcam images and thermographs in real-time. The image frequency in the experiment was set at 2 FPS. This image acquisition frequency was selected on the basis of the length of experiment and image acquisition was carried out for the whole length of the simulation scenario.
Mounting of the IRISYS imager

The infrared imager was the main instrument used to acquire driver information during the experiment. The infrared imager and visual camera were mounted close together on a test rig. The camera was positioned on the left (passenger side) windscreen pillar making an angle of 60 Degrees with the longitudinal direction. The lens field of view (FOV) was 20 degrees and the IR camera was mounted 1 metre away approximately from the seat head rest. With the image capturing 355 mm square from the angled position, it manages to acquire the face, shoulders and arm with the hands on the upper half of the steering wheel.

Visual camera

A visual (CMOS) web camera was used for the purpose of adjusting the field of view of the IR imager and for verification of the results taken from the IR imager after processing.

Driving simulator

The driving simulator comprised a custom built test rig with front projection screen and adjustable driving controls (Figure 7). A separate control room housed a driver communication system and the STISIM® driving simulation software on an IBM PC. The driver was kept in contact with the researcher by means of the driver communication system during the length of the experiment. The STISIM® driving simulator was programmed for the MS-DOS operating system. The simulator is designed such that it provides the driver with realistic driving experience using both the visual display and audio effects as feedback to driver actions.
Scenario

The scenario selected for the experiment involved urban busy traffic, lasting for approximately 20 minutes. An urban traffic scene was selected because the number of tasks during driving is much higher than for motorway or trunk road driving. The scenario involved a number of tasks performed by the volunteer as well as going through the driving simulation. These tasks included putting a seat belt on, adjusting mirrors, looking in the rear view mirror, looking left or right, using a swipe card to simulate entering a secured car park, mobile phone usage while driving and using an in-car stereo system or climate control. These tasks were in addition to other conventional driving tasks, such as looking left or right before making a turn, arriving at traffic lights and waiting for a signal, lane changing manoeuvres and looking at side and rear view mirrors.

A second scenario was conducted for monitoring fatigue and sleepiness in drivers while driving for longer periods. A long road with curves was programmed in a scenario which lasted for over 50 minutes and curtains were drawn over the simulator test rig to give the driver a sense of driving alone. Noise was cut to a minimum, less traffic was shown on the road and the drivers were asked to maintain a constant speed of 60 mph.

5 EXPERIMENTAL RESULTS

5.1 ANN Simulation

The simulation set was three times the size of the training data set. Simulation set results are plotted in Figures 8, 9 and 10. The plots are for a single human subject, chosen to represent an average identification accuracy rate. The different postures
in the graphs are linked with the numerical postural code, or p-code - the closer the actual result plot is to the posture code the more accurate is the detection.

Each driver volunteer is considered individually for ANN training, therefore the system can detect the same posture with similar accuracy for all subjects. This means that a person with long hair or short hair will not have different accuracies in the system due to the thresholding of thermographs and individual driver training, as there are 3 different regions, which are combined together to get the final result. The posture detection algorithm will be running at 4 FPS, i.e. analysing four (4) thermographs each second. If one thermograph ANN output result shows abnormality or inaccuracy, the remaining three (3) thermographs may be able to remove the abnormality or inaccuracy. This makes the safety system is reliable and robust. The safety system in real life needs to be a real time which would provide information to the intelligent central safety system to provide feedback to the driver.

5.2 Real life data comparison with results

Video footage of 20 volunteers was taken driving in urban areas and later on a motorway. Ten volunteers were below the age of 45, whereas the other 10 were over the age of 55. The groups of volunteers were 50% male and 50% female. Each video lasted for at least 45 minutes depending upon the time each volunteer took to drive from start to finish.

The video footage of each volunteer was analysed by taking a movement description and the time taken and also the p-code was identified and noted. A particular pattern of movements relates to the p-code generated during the video analysis. The movement for each motion detected may be a single event, for example like looking right, or it could be a series of movements to carry out a particular manoeuvre, like
putting on a seat belt. This series of movements will create a pattern for that manoeuvre which is more or less the same for most drivers. A few examples of the patterns of motion with p-codes follow in Table 3. The larger manoeuvres are broken down into smaller movements which the safety system detects.

<table>
<thead>
<tr>
<th>Task</th>
<th>Time</th>
<th>P-Code</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Applying Handbrake</td>
<td>2 s</td>
<td>D-L-S</td>
<td>One hand on steering wheel</td>
</tr>
<tr>
<td>2 Left Turn (T-Junction or Cross Road)</td>
<td></td>
<td></td>
<td>Subject brakes and carries out following movement</td>
</tr>
<tr>
<td>Look Right</td>
<td>3 s</td>
<td>N-R-S</td>
<td>Less traffic</td>
</tr>
<tr>
<td>Turn Left (Driver looks ahead)</td>
<td>1 s</td>
<td>N-F-S</td>
<td></td>
</tr>
<tr>
<td>3 Left Turn (T-Junction or Cross Road)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Look Right</td>
<td>6 s</td>
<td>N-R-S</td>
<td>Heavy traffic from right</td>
</tr>
<tr>
<td>Turn Left (Driver looks ahead)</td>
<td>1 s</td>
<td>N-F-S</td>
<td></td>
</tr>
</tbody>
</table>

Table 3. Examples of driver positions found from the videos
6 DISCUSSION

Low resolution infrared imaging has been shown to be an effective means of monitoring driver posture and movements to provide a number of important physical indicators of driving behaviour. IR imaging is a practical and non-intrusive method of occupant tracking which does not invade the privacy of individuals in the way that visual imaging may be perceived to do and, therefore, should be ethically acceptable. The system using neural network analysis has been shown to be robust. IR imaging has the advantage of being entirely independent of lighting conditions. The low resolution allows hardware costs to be kept down and further reductions will be possible by design for mass production to achieve appropriate cost levels for mid-range and, ultimately, smaller cars.

The low resolution means that this safety system cannot detect eye gaze or small movements of the driver’s head. Eye gaze can be anything from looking in the side and rear view mirrors to observing scenes on the road. The imaging system as developed can identify 18 different driver postures or movements and reliably interpret these in the form of p-codes. Single frame analysis can then provide valuable information on occupancy and position, for example OOP drivers, the driver’s physique and eye height estimates, all of which are important considerations for safe airbag deployment. Further analysis based on time histories will be able to identify a range of high risk situations. For example impaired movements can cause difficulty in turning the head sufficiently for adequate vision at junctions and for checking of blind spots. Poor trunk stability can cause lack of confidence and degraded car control. These are typical problems encountered by many older people or people impaired by disability or injury.

Although it may be used in a stand-alone mode the greatest potential of the IR imaging system will be realised as part of an integrated multi-sensor intelligent safety
system. The interpretation or significance of events and behaviours will clearly depend to an extent on the state of the vehicle, for example whether it is stationary or in motion, driving straight or turning. Simply linking the IR system with road speed, throttle and braking information is straightforward and low cost and can provide a rich data source which can be used to identify high risk situations or behaviours, such as evidence of drowsiness or time with attention away from the road while the vehicle is in motion.

This research has shown that a low resolution 16 by 16 pixel IR imager can play a significant role in the next generation of intelligent safety systems.

REFERENCES


**APPENDIX 1**

**Notation**

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANN</td>
<td>artificial neural network</td>
</tr>
<tr>
<td>$f_i$</td>
<td>known values on the grid at points $(q_i)$</td>
</tr>
<tr>
<td>FPS</td>
<td>frames per second</td>
</tr>
<tr>
<td>IR</td>
<td>infrared</td>
</tr>
<tr>
<td>$L_j(q)$</td>
<td>Lagrange polynomial</td>
</tr>
<tr>
<td>LWIR</td>
<td>long wavelength infrared</td>
</tr>
<tr>
<td>MLP</td>
<td>Multi-layer perceptron</td>
</tr>
<tr>
<td>OOP</td>
<td>out of position</td>
</tr>
<tr>
<td>p-code</td>
<td>a unique letter code describing a body position</td>
</tr>
<tr>
<td>P(q)</td>
<td>interpolated value</td>
</tr>
<tr>
<td>q</td>
<td>point at which interpolation takes place</td>
</tr>
<tr>
<td>R1</td>
<td>segmented region of the image forward of the driver</td>
</tr>
<tr>
<td>R2</td>
<td>segmented region of the image containing the driver's head</td>
</tr>
<tr>
<td>R3</td>
<td>the lower segmented region of the image</td>
</tr>
<tr>
<td>RBN</td>
<td>Radial basis network</td>
</tr>
<tr>
<td>SOM</td>
<td>Self organizing map</td>
</tr>
</tbody>
</table>
List of figure captions

Figure 1. System flow chart for the position tracking algorithm
Figure 2. Infrared data acquisition software
Figure 3. Four types of interpolated infrared image
Figure 4. Histogram of an infrared thermograph
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Figure 7. Driving simulator test rig
Figure 8. ANN simulation result for torso region R1
Figure 9. ANN simulation result for head region R2
Figure 10. ANN simulation result for arm and shoulder region R3

Table 1. Posture codes

Table 2. Neural Network construction specifications

Table 3. Examples of driver positions found from the videos
Figure 1. System flow chart for the position tracking algorithm
Figure 2. Infrared data acquisition software
Nearest Interpolation  Cubic Interpolation
Linear Interpolation  Spline Interpolation

Figure 3. Four types of interpolated infrared image
Figure 4. Histogram of an infrared thermograph
Interpolated thermograph

Thermograph divided into three regions R1, R2 and R3

Figure 5. Region allocation within the infrared image
Figure 6. Feature selection process

Specifications of driver posture list which is being detected (P-codes)

Image processing block

Infrared image
Segmentation of body region
Division of infrared image into three regions

Features extracted from region 1
Features extracted from region 2
Features extracted from region 3

List of features narrowed down by comparing different infrared images

Plotting of features against each feature (using scatter-gram, graphs)

Decision curves drawn and graphs compared

Selected features from region 1
Selected features from region 2
Selected features from region 3
Figure 7. Driving simulator test rig
Figure 8. ANN simulation result for torso region R1
Figure 9. ANN simulation result for head region R2
Figure 10. ANN simulation result for arm and shoulder region R3