

**Towards Context-based Fatigue Detection System in
Vehicular Area Network**

by

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A thesis Submitted to the

Faculty of Graduate and Postdoctoral Studies

In partial fulfillment of the requirements

For the Degree of Master in Computer Science

Ottawa-Carleton Institute for Computer Science

School of Electrical Engineering and Computer Science

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Abstract

Driver fatigue is responsible for up to 30% of fatal car accidents. This issue has been addressed by many scholars in order to save thousands of lives and reduce many costs. The goal of this work is to reduce the number of car accidents caused by mental fatigue or drowsiness. In order to achieve this goal, we propose a personalized Bayesian Network (BN) to detect driver's fatigue. The detection of driver fatigue is enhanced by combining data that reflects the driver's performance with context-aware information. The parameters of the system are the angular velocity of the steering wheel, the pressure applied to the gas and brake pedals, the grip force on the steering wheel, weather conditions, current traffic, and time of day. The aforementioned parameters of the network are updated on a regular basis, which makes fatigue detection more reliable. Besides, these parameters allow the system to detect a driver's fatigue through driving performance which is both individualized and context aware. In our experiment, subjects drove a driving simulator game during six sessions, for a total of one hour. After each session, every subject used the Karolinska Sleepiness Scale (KSS) to rate her fatigue's level. The system was trained on the data collected separately from each user, allowing BN to be personalized for each subject. The proposed system showed an average accuracy of 96%, and ability to overcome the issue of individual differences and uncertainties which are involved in fatigue detection process.

Acknowledgements

I would like to convey my sincere appreciation and gratitude to my supervisor, Prof. Abdulmotaleb El Saddik, for providing the opportunity and support to pursue my master's studies. His guidance, patience, words of encouragement and valuable comments have been invaluable and helpful to me in all the time of studies.

Besides my supervisor, I am grateful to Dr. Jamal, for his invaluable help and feedback, hours of meetings and discussions, and his patience. Without his support and assistance, this thesis would not have been possible. I am also thankful to Dr. Dewan who for his guidance and invaluable feedback that was very helpful to me.

Moreover, I would like to express my heart-felt gratitude to my father, Saud, and my mother, Najiah, for their encouragement, prayers for me and persistent support throughout my life. Also, there are no words can express my love and appreciation to my fiancée, Seham, for all the precious support, patience, and words of encouragement. Indeed, I'm very thankful to have her in my life.

Special thanks to my best friends and my colleagues at Discover and MCRLab for their comments, help, and encouragement, and the good time we had. Also, a special thanks to Saudi Cultural Bureau for the scholarship and the generous finance support.

Lastly, I dedicate this work to my fiancée, Seham.

Table of Contents

Towards Context-based Fatigue Detection System in Vehicular Area Network	i
Abstract.....	ii
Acknowledgements.....	iii
Table of Contents	iv
List of Figures.....	vii
List of Tables	ix
LIST OF ABBREVIATION	x
Chapter 1 Introduction.....	1
1.1 Objective.....	1
1.2 Significance of the Problem.....	2
1.3 Background and Motivation.....	3
1.4 Research Problem.....	4
1.5 Thesis Contribution.....	5
1.6 Scholarly Achievements.....	6
1.7 Thesis Outlines.....	6
Chapter 2 Background and Related Work.....	7
2.1 Fatigue Definition	7
2.2 Who is More at Risk of Fatigue	8
2.3 Fatigue Categories	8
2.4 Causes of Fatigue	10
2.4.1 Sleep Deprivation	10
2.4.2 Time on Task.....	11
2.4.3 Time of Day	12
2.4.4 Monotony of Road.....	12
2.4.5 Drivers' Age.....	13

2.5 Characteristics of Sleep-Related Accidents.....	14
2.6 Practical Countermeasures.....	15
2.6.1 Rolling Down the Window/ Turning up the Volume on the Sound System	15
2.6.2 Nap	16
2.6.3 Break	16
2.6.4 Caffeine.....	16
2.7 Fatigue Detection.....	17
2.7.1 Methods Based on Driver Performance.....	18
2.7.2 Method Based on Driver’s State	25
2.8 Criteria of Fatigue Detection Systems Based on Driving Performance.....	30
Chapter 3 Bayesian Network	33
3.1 Definition.....	33
3.2 Why a Bayesian Network	33
3.3 Uncertainties.....	35
3.3.1 Parameters Learning	35
3.4 Inference.....	36
3.5 Example of Bayesian Network	36
Chapter 4 Proposed System.....	41
4.1 Requirements.....	41
4.2 Architecture Overview.....	42
4.3 PBN Parameters	45
4.3.1 Maximum Angular Velocity of the Steering Wheel	46
4.3.2 Average Angular Velocity of the Steering Wheel	46
4.3.3 Maximum Pressure Applied to the Gas Pedal.....	47
4.3.4 Average Pressure Applied to the Gas Pedal	48
4.3.5 Maximum Pressure Applied to the Brake Pedal.....	48
4.3.6 Average Pressure Applied to the Brake Pedal.....	48
4.3.7 Grip Force.....	49
4.3.8 Time of Day.....	49
4.3.9 Weather and Traffic	50

Chapter 5 Experiment Setup	51
5.1 Apparatus.....	51
5.2 Software.....	52
5.3 Karolinska Sleeping Scale	53
5.4 Experiment Hypothesis	55
5.5 Experiment Protocol.....	56
5.6 Data Collection and Discretization	56
Chapter 6 Analysis of the Data and Testing.....	60
6.1 Analysis of the Data.....	60
6.1.1 Steering Wheel.....	60
6.1.2 Gas Pedal.....	67
6.1.3 Brake Pedal	70
6.1.4 Grip Force	72
6.2 Testing the System.....	75
6.3 System Accuracy.....	79
6.3.1 Personalized BN.....	81
6.3.2 Generalized BN.....	81
Chapter 7 Conclusion and Future Work	85
7.1 Conclusion	85
7.2 Limitations	86
7.3 Future Work.....	86

List of Figures

Figure 2-1: Fatigue Categories.....	9
Figure 2-2: Causes of Fatigue	10
Figure 2-3: Fatigue detection technique.....	18
Figure 2-4: Early and late driver steering behaviour in the time domain (King et al., 1998) .	20
Figure 2-5: Frequency of large steering wheel movements (Thiffault & Bergeron, 2003). ...	21
Figure 2-6: The effect of caffeine and time on bed on driving performance.....	24
Figure 3-1: DAG wet grass.	37
Figure 3-2: The conditional independency of the nodes in DAG of wet grass.....	38
Figure 4-1: An overview of the system architecture.	42
Figure 4-2: DAG of the proposed system.	43
Figure 5-1: (a): Arduino microcontroller board. (b): Force sensing sensor. (c) Super Sports 3X.....	52
Figure 5-2: A screenshot of the 3D driving simulator game.....	53
Figure 6-1: Maximum angular velocity (degree/second).....	62
Figure 6-2: Maximum angular velocity	63
Figure 6-3: Average angular velocity	65
Figure 6-4: Average angular velocity (degree/second).....	66
Figure 6-5: Average pressure applied to the gas pedal.	69
Figure 6-6: Average pressure applied to the gas pedal.	70
Figure 6-7: Average pressure applied to the brake pedal.....	72
Figure 6-8: Average grip force.....	74
Figure 6-9: Average grip force.....	75
Figure 6-10: A screenshot of the system.....	76
Figure 6-11: Conditional probability tables of different users.	77
Figure 6-12: A screenshot of the system after updating the parameters.	78
Figure 6-13: A screenshot of the inferring (entering of evidence).....	79

Figure 6-14: A screenshot of the system after updating the parameters of all the users.....83

Figure 6-15: A screenshot of the system after increasing the nodes' states.....84

List of Tables

Table 2-1: (Ingre, ÅKerstedt, Peters, Anund, & Kecklund, 2006).	23
Table 2-2: EEG signal characteristics.	27
Table 5-1: KSS.	54
Table 6-1: Average maximum angular velocity (degree/second).	61
Table 6-2: Average angular velocity (degree/second).	64
Table 6-3: Average pressure applied to the gas pedal.	68
Table 6-4: Average pressure applied to the brake pedal.	71
Table 6-5: Average grip force.	73
Table 6-6: Average accuracy for the users.	81

LIST OF ABBREVIATION

BN	Bayesian Network
CPT	Conditional Probability Table
DAG	Directed Acyclic Graph
ECG	Electrocardiogram
EEG	Electroencephalography
KSS	Karolinska Sleepiness Scale
MSA	motorway service area
NHTSA	National Highway Traffic Safety Administration
NREM	Non-Rapid Eye Movement
NTSB	National Transportation Safety Board
PERCLOS	Percent Eyelid Closure
PBN	Personalized Bayesian Network
REM	Rapid Eye Movement
SDLP	Standard Deviation of Lateral Position
SVM	Support Vector Machine

Chapter 1 Introduction

According to statistics, there are over a billion vehicles around the world (Sousanis, J. 2007), and approximately 20 million in Canada only (Statistics Canada, 2007). These numbers demonstrate the importance of transportation safety. Manufactures and governments around the world have been contributing to transportation safety by equipping vehicles with many safety features and by creating government legislation. Some legislation mandates the use of certain car safety features such as seat belts, while others make specific features a standard in all cars.

Despite current safety features and legislation, statistics show that many fatal car accidents still occur around the world. Drivers are the primary cause of a considerable proportion of these accidents. Indeed, fatigued driving is to blame for up to 30 percent of accidents (The Royal Society for the Prevention of Accidents, n.d.). When driving, a split second reaction may help avoid an accident, which is why detecting a driver's fatigue before an accident occurs may save thousands of lives and reduce many costs.

1.1 Objective

The aim of this work is to create a Personalized Bayesian Network (PBN) that uses data from different sensory inputs such as force sensing of the steering wheel, force applied on a pedal, weather information. This data can be acquired from modern cars since they have advanced sensors and computing facilities controlling their functions. Moreover, the proposed fatigue

detection system should overcome the issues of individual differences and uncertainties that are involved in the fatigue detection process.

In order to be possible to be applied in today's cars and to provide comfort to the driver, the proposed PBN uses non-intrusive/non-wearable sensors. Besides, it does not require the use of cameras since they might be affected by other factors such as lightening and wearing sunglasses.

1.2 Significance of the Problem

Statistics show that 25-30% of accidents are caused by driver fatigue or drowsiness (The Royal Society for the Prevention of Accidents, n.d.). The US National Highway (NHTSA, n.d.) statistics show that approximately 100,000 crashes each year are fatigue related accidents. Approximately 1,000 people die and 40,000 people get injured as a result of accidents involving drowsiness or fatigue (NHTSA, n.d.).

In 2003, the NHTSA conducted phone interviews with 4,010 drivers. Thirty-seven percent of the drivers interviewed admitted they have nodded off or fallen asleep at least once while driving, and 29% of those drivers have had such an experience in the previous six months. Similarly, 14.5% of Ontario drivers, 145,000 drivers, have reported that they have nodded off or fallen asleep while driving at least once in their lives, while 60% have driven while being fatigued (Traffic Injury Research Foundation, n.d.).

The 1990 NTSB study of 182 heavy truck accidents that were fatal to drivers showed that fatigue was the primary cause for 31% of those accidents (Board, n.d.).

In England, 16-20% of accidents have been reported by police as sleep-related accidents (J A Horne & Reyner, 1995). Research shows that 90% of sleep-related accidents can be avoided if the driver is alerted one second before the accident occurs (Fan, Yin, & Sun, 2007).

1.3 Background and Motivation

Fatigue can be detected through various signs such as yawning, nodding off, a deterioration of performance, and others. Some of the physiological signs may require a wearable or intrusive sensor to detect, as is the case with EEG. Also, fatigue detection through driving performance involves many uncertainties. For example, several studies concluded that an increase in the standard deviation in lateral position (SDLP) indicates fatigue. Yet, some fatigued users showed no increase in SDLP and others only had an insignificant increase. Uncertainties in detecting fatigue may be clearer to the reader by addressing questions such as how many yawns are needed or how many times a driver has to nod off before the alarm is triggered. In other words, how do we calculate performance deterioration? Furthermore, individual differences may further complicate the process of detecting fatigue. Some signs may also appear earlier than other signs. For instance, running off lane is considered a late sign, resulting from severe fatigue. Detecting fatigue in its early stages is essential to provide enough time for the driver or the system to handle the situation.

This study aims to contribute to the safety of transportation by proposing a system to detect driver's fatigue accurately. The proposed system does not use wearable or intrusive sensors, in order to make the system more comfortable for drivers and to make it possible to install in cars. The system also has several features that contribute to its reliability and help overcome fatigue detection challenges such as individual differences and uncertainties.

1.4 Research Problem

Driver fatigue detection can be a complicated process. In recent years, different systems and approaches using various techniques have been proposed to detect driver fatigue. However, some issues need to be addressed in order to find a suitable detection system. These issues are: individual differences, the ability to work under various conditions, and avoiding the use of intrusive or wearable sensors. Most importantly, driver fatigue needs to be detected accurately. Therefore, finding a fatigue detection system that can overcome the aforementioned obstacles and detect fatigue accurately has been one of the most important issues to be solved.

Driving performance deteriorates due to fatigue. Therefore, fatigue can be detected through driving performance. However, there are some obstacles in detecting fatigue through driving performance. These obstacles may be addressed by determining how to assess performance deterioration or how to measure driving performance. In addition, this process is further complicated since driving styles differ from one driver to another. Moreover, monitoring

driver's performance may require other sensors such as cameras and radars. For example, via camera, a system can detect if the driver goes off lane, which could be considered as a sign of fatigue. However, finding an efficient and simple approach to detecting fatigue through driving performance is one of our objectives.

We concluded that driving data from the steering wheel and the pedals can be used to detect driving performance; the issue is how to translate these data to identify fatigue.

Indeed, this draws the attention to the uncertainties that are involved in this process. Raw data from the steering wheel and the pedals would be merely numbers. For instance, if x and y represent data acquired from the steering wheel and the pedals, how can we infer a driver's awareness? Besides, it would rarely be repeated. For example, even if a driver drives on the same track repeatedly, the recorded driving data would rarely be identical.

1.5 Thesis Contribution

- Detecting fatigue through driving performance by the design and development of a Bayesian Network that uses different context sources to detect fatigue such as steering wheel, pedals, weather and force sensing sensor.
- Design and Validation process of the proposed system based on a driving game simulator. The results showed an average accuracy up to 96%, and ability to overcome the issue of individual differences and uncertainties.

1.6 Scholarly Achievements

Sultan Alhazmi, Dewan Tanvir Ahmed, Jamal Saboune and Abdulmotaleb El Saddik, “A Multimodal Personalized Fatigue Detection System in Vehicular Area Network”, submitted to Springer Multimedia Tools and Applications.

1.7 Thesis Outlines

The remainder of the thesis is organized as follows:

Chapter 2 provides an overview of fatigue, including definitions and causes. It also presents other approaches and techniques that were used to detect fatigue. Furthermore, it presents the criteria of fatigue detection systems based on driving performance, as well as some characteristics of fatigue related accidents.

Chapter 3 starts with a brief overview of Bayesian Network including an example.

Chapter 4 presents a fatigue detection system and describes its key parameters.

Chapter 5 focuses on analyzing and discussing the acquired data and the results.

Finally, Chapter 6 provides a conclusion and possible future work as well as limitations.

Chapter 2 Background and Related Work

2.1 Fatigue Definition

In the literature reviews, there is a lack of an agreed definition for fatigue. In the medical dictionary, the term fatigue is defined as: “physical and/or mental exhaustion that can be triggered by stress, medication, overwork, or mental and physical illness or disease.” According to that definition, fatigue can be classified as physical or mental fatigue. (Shen, Barbera, & Shapiro, 2006) define physical fatigue as: “a loss of maximal force-generating capacity during muscular activity, or a failure of the functional organ”. While defining mental fatigue as: “a state of weariness related to reduced motivation”.

The term fatigue in this thesis refers to mental fatigue, and it may be used interchangeably with the term sleepiness. Fatigue is a state of decreased awareness or alertness that may result from neurobiological processes organizing circadian rhythms, prolonged and monotonous driving, or sleep deprivation. Since driving can be considered as a vigilance task, drivers may be unaware of their environment, miss some road signals or make wrong decisions due to a vigilance decrement as a result of fatigue (Milosevic, 1997). Also, they may take a longer time to react and their attention span decreases. In extreme cases of fatigue, drivers may experience microsleeps, which are periods of a few seconds of sleep, and the results of microsleeps could be fatal.

2.2 Who is More at Risk of Fatigue

Drivers who are probably at risk of sleep-related accidents:

- Young drivers, 25 years old or younger, are more likely to drive late at night and be sleep deprived (Pack et al., 1995).
- Older people, 60 years old or older, might be more prone to fatigue than other drivers (Campagne, Pebayle, & Muzet, 2004).
- Drivers who have a sleep disorder (Young, Blustein, Finn, & Palta, 1997).
- Drivers who are taking medicine with drowsiness as a known side effect (Logan, Case, Gordon, & others, 2000) (Neutel, 1995).
- People who work at night or have irregular, rotating shifts (McCartt, Ribner, Pack, & Hammer, 1996).
- Commercial drivers/truck drivers (McCartt et al., 1996).

2.3 Fatigue Categories

Fatigue can be categorized based on the causes into sleep-related and work-related as shown in Figure 2-1. *Sleep-related fatigue* is affected by sleep deprivation, time of day, and sleep restrictions. On the other hand, *work-related fatigue* can be passive or active fatigue, depending on the cause. Driving in bad conditions such as bad weather, poor visibility or dense traffic may increase the mental overload of the driver, resulting in active fatigue, which is considered to be the most common type of work-related fatigue. Another cause of active fatigue is doing another task while driving, for example searching for an address.

Passive fatigue may occur when a driver drives on monotonous roads or for a long period of time, especially with low traffic (May & Baldwin, 2009).

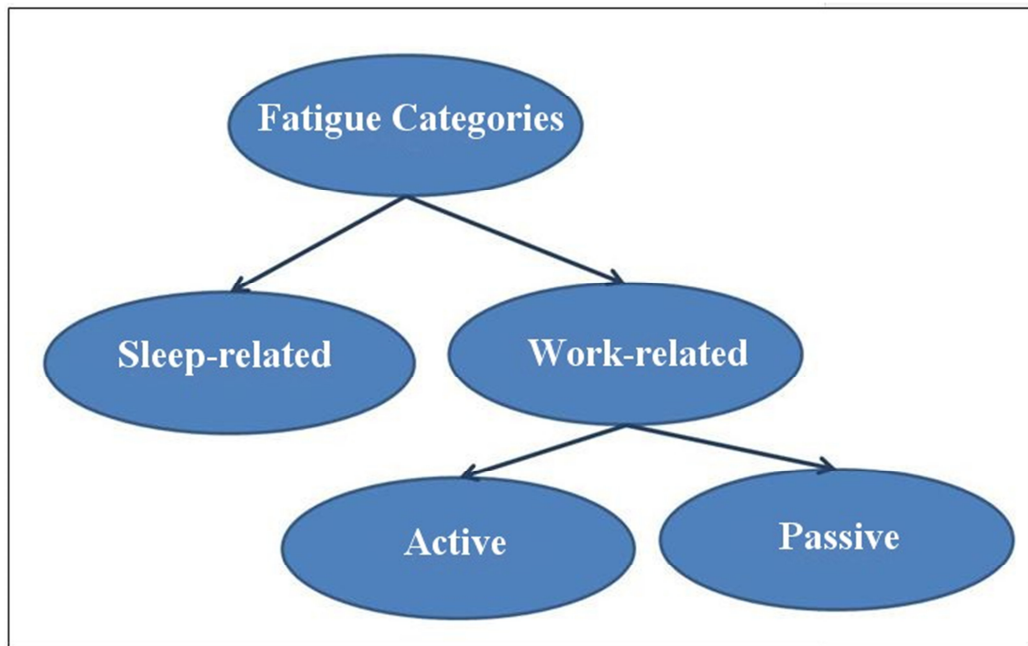


Figure 2-1: Fatigue Categories

2.4 Causes of Fatigue

Fatigue has several causes. For instance, sleep deprivation, time on task, time of day, monotony of road, and driver's age are factors that cause fatigue as shown in Figure 2-2.

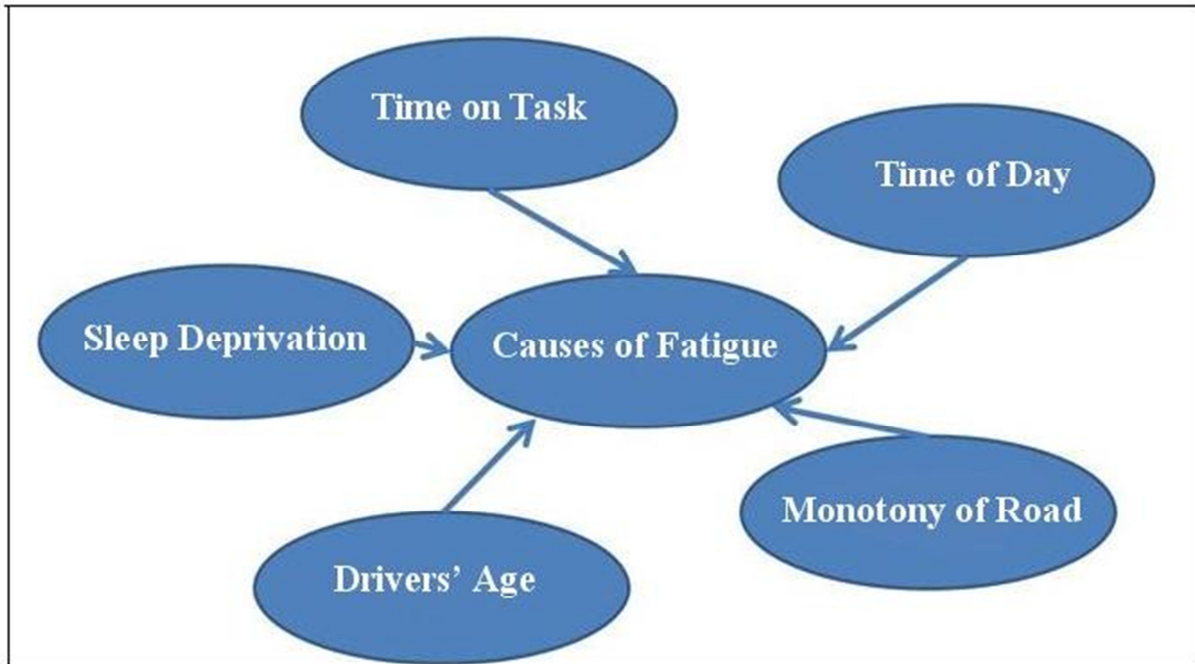


Figure 2-2: Causes of Fatigue

2.4.1 Sleep Deprivation

Sleep deprivation, or lack of sleep, is the most common cause of sleepiness. (Naitoh, 1989) concluded that sleeping less than 4 hours per night can significantly impair the driving performance of individuals. Also, (De Valck & Cluydts, 2001) concluded that partial sleep deprivation can impair the driving performance by increasing lane and speed deviations.

Also, (Stutts, Wilkins, Scott Osberg, & Vaughn, 2003) indicated that sleeping less than 5 hours per night increases the probability of being involved in a sleep-related accident by nearly five times.

Moreover, fragmented sleep or sleep disruptions cause loss of sleep, which may eventually result in sleep deprivation (Dinges, 2009). Loss of sleep, indeed, increases the probability of falling asleep at the wheel and impairs the driving performance (Mitler, Miller, Lipsitz, Walsh, & Wylie, 1997) (Wilkinson, Edwards, & Haines, 1966).

2.4.2 Time on Task

Several studies demonstrated the strong relationship between fatigue and time on task, as in (Thiffault & Bergeron, 2003). According to (Mackie & Miller, 1978), the performance of truck drivers starts to deteriorate after 5 hours of driving with irregular schedules as opposed to 8 hours of driving with regular schedules. Commercial, bus, and truck drivers are not free to determine their own work schedule; therefore, their irregular shift hours may require them to drive at night, which increases the risk of an accident due to severe sleepiness (Åkerstedt, 1995). Also, irregular shift hours negatively impacts a driver's rest and sleep time. A study conducted by (Åkerstedt, Kecklund, Gillberg, Lowden, & Axelsson, 2000) suggests having recovery periods based on the duration of the irregular work schedule.

Furthermore, (Harris & Mackie, 1972) conducted a study that showed that the risk of being in a sleep-related accident increases after 4 hours of continuous driving. Also, the studies of (Ting, Hwang, Doong, & Jeng, 2008) and (Otmani, Pebayle, Roge, & Muzet, 2005) showed that prolonged driving significantly deteriorated driving performance. The duration time of the driving has a strong effect on fatigue.

2.4.3 Time of Day

People feel sleepy during the afternoon, (2-4 pm), and the morning (2-6 am) hours due to circadian rhythms. These effects are felt even by those who are not sleep deprived (Dinges, 2009). (Mitler et al., 1997) has also found a correlation between time of day and fatigue.

(Moller, Kayumov, Bulmash, Nhan, & Shapiro, 2006) concluded that the frequency of micro sleeps, 3sec or more, was higher in the afternoon.

Furthermore, a study by (ÅKERSTEDT, PETERS, Anund, & KECKLUND, 2005) showed that the driving performance of night shift workers was impaired after their shift, making them more vulnerable to sleep-related accidents.

2.4.4 Monotony of Road

According to (McBain, 1970), a situation or environment can be considered monotonous when stimuli remains unchanged, is repetitive, or is predictable. An example of monotonous

driving would be driving on highways, especially at night. In this case, drivers would be vulnerable to sleep-related accidents (Gillberg, Kecklund, & Åkerstedt, 1994). According to (McCartt et al., 1996) 40% of sleep-related accidents occur on highways. Also, 57% of fatal accidents in Canada occurred on highways (CCMTA, 2010).

In a simulator-based study conducted by (Thiffault & Bergeron, 2003), sleep-related behaviour was clearly observed after 20 minutes of driving, when the driving environment or scenario was monotonous.

2.4.5 Drivers' Age

The age of a driver may be considered to be a factor for making the driver more vulnerable to fatigue. (Campagne et al., 2004) compared the driving performance of three age groups, 20-30, 40-50 and 60-70. The results of the study showed that the deterioration of vigilance is associated with driving errors for drivers who are 60 years old and above.

Yet, (Pack et al., 1995) analyzed the database of sleep-related accidents that took place between 1990-1992, and found that 55% of the accidents involved drivers 25 years old or younger.

The studies show that older people may be more vulnerable to sleep-related accidents, but falling asleep at the wheel can happen to anyone. Moreover, younger people may be more reckless, or their sleep unorganized or fragmented, which could explain their involvement in 55% of sleep-related accidents.

2.5 Characteristics of Sleep-Related Accidents

Sleep-related accidents can be identified by certain criteria. (J A Horne & Reyner, 2009) identified some of those criteria, which include running off the road, no brake marks, no mechanical fault, and good driving conditions.

(Pack et al., 1995) also investigated the characteristics of sleep-related accidents. The main characteristics of sleep-related accidents that happened between 1990 and 1992 were: driving off the road, single vehicle accidents, and an excess of speed as well as the time of the accident.

The time of the accident can be an indicator of sleep-related accidents. Some statistics show that the highest number of accidents occur in the middle of the night, in the early morning, and between 3-6pm (Pack et al., 1995). The possibility of the driver being fatigued or drowsy at these times is very high. Many sleep-related accidents occur on high-speed roads, especially in non-urban areas. The monotony of these roads, along with prolonged driving could explain the high number of accidents.

Moreover, fatigue can decrease performance and vigilance and slow the reaction time of individuals (Dinges, 2009). There may therefore be accidents that were attributed to loss of attention such as not seeing a road sign, which could, in reality, be a result of fatigue.

(Hamouda & Saccomanno, 1995) developed a neural-network model that can identify the patterns in sleep-related accidents. The model was trained on data from truck accident

records in Ontario. The model was successfully able to detect whether the accident was sleep-related or not, based on the similarities in the conditions of sleep-related accidents.

2.6 Practical Countermeasures

According to (L A Reyner & Horne, 1998) sleep is not known to suddenly occur, bringing people from an alert state to a sleep state, except in rare medical conditions. In other words, healthy drivers, who do not have rare medical conditions such as narcolepsy, do not encounter sudden sleep. Therefore, sleepy drivers are aware of their sleep level, though they might underestimate the chances of falling asleep while driving. Drivers who feel sleepy often use sleep countermeasures, to stop the process of falling asleep or to increase their awareness. There are several countermeasures for sleep, yet the optimal solution for fatigue is to stop driving (James A Horne & Baulk, 2003).

2.6.1 Rolling Down the Window/ Turning up the Volume on the Sound System

Some countermeasures such as rolling down the window or turning up the volume of the sound system may have only a temporary benefit. Indeed, turning up the volume of the radio in this case may distract fatigued drivers from the fact that their driving is impaired due to fatigue (J A Horne & Reyner, 2009).

2.6.2 Nap

Taking a nap is considered to be a good countermeasure. Naps depend on several variables such as the circadian rhythms influence, the period of time spent awake since the last sleep, and the quality of the last sleep. These variables can be taken into consideration to determine the minimum amount of sleep required to avoid any delays or tardiness, especially for drivers who follow a schedule, such as truck drivers (J A Horne & Reyner, 2009). (Naitoh, Kelly, & Babkoff, 1990) concluded that having a 20 minute nap every six hours over a period of 35 hours can be very beneficial to a driver's performance.

2.6.3 Break

Having a break is also considered a good countermeasure since it required that we stop driving. Some motorways in the UK are facilitated by Motor Service Areas (MSAs), which are located 30KM apart along motorways. MSAs have large parking areas, restaurants, shops and picnic areas. (L A Reyner, Horne, & Flatley, 2010) conducted a study to evaluate the effectiveness of the Motorway Service Areas (MSAs) in reducing fatigue-related accidents. The results showed that MSAs are significantly effective in reducing sleep-related accidents.

2.6.4 Caffeine

Caffeine is a non-prescription stimulant that stimulates neurons involved in vigilance and inhibits neurons involved in sleep (Biggs et al., 2007). It takes approximately 45 minutes for

caffeine to be completely absorbed in the human body (Mets, Baas, Van Boven, Olivier, & Verster, 2012). Several research studies demonstrate its ability in postponing sleep and also in reducing fatigue that may result from repetitive tasks or monotonous driving. Consuming 200 mg of caffeine, which can be obtained from 2-3 cups of coffee, 30 minutes before driving, can be effective in reducing sleepiness when driving in the early morning, for drivers who had 5 hours of sleep. According to the study, this effect can last up to 2 hours. A smaller dosage of caffeine, 100mg, is also found to be quite effective in reducing sleepiness and lane drifting in the simulated study (Louise A Reyner & Horne, 2000), (Åkerstedt & Ficca, 1997), (Biggs et al., 2007). A recent study on the effects of caffeine on driving performance showed that 300mg of slow-released caffeine was an effective countermeasure. The 300mg of slow-released caffeine improved drivers' performance in terms of a decrease in lane and speed deviations. The effect of the caffeine began after one hour, and lasted for 5 hours. The long duration of the effect is due to the slow-release of the caffeine (De Valck & Cluydts, 2001).

2.7 Fatigue Detection

The techniques used to detect fatigue can be broadly categorized into three categories as shown in Figure 2-3. First, techniques based on driver's current state, such as eyelid movements, yawning, heart rate and body temperature. Second, techniques based on the driver's performance, such as steering wheel movements and lane tracking. The third category is techniques based on both the driver's current state and the driver's performance (Wang, Yang, Ren, & Zheng, 2006).

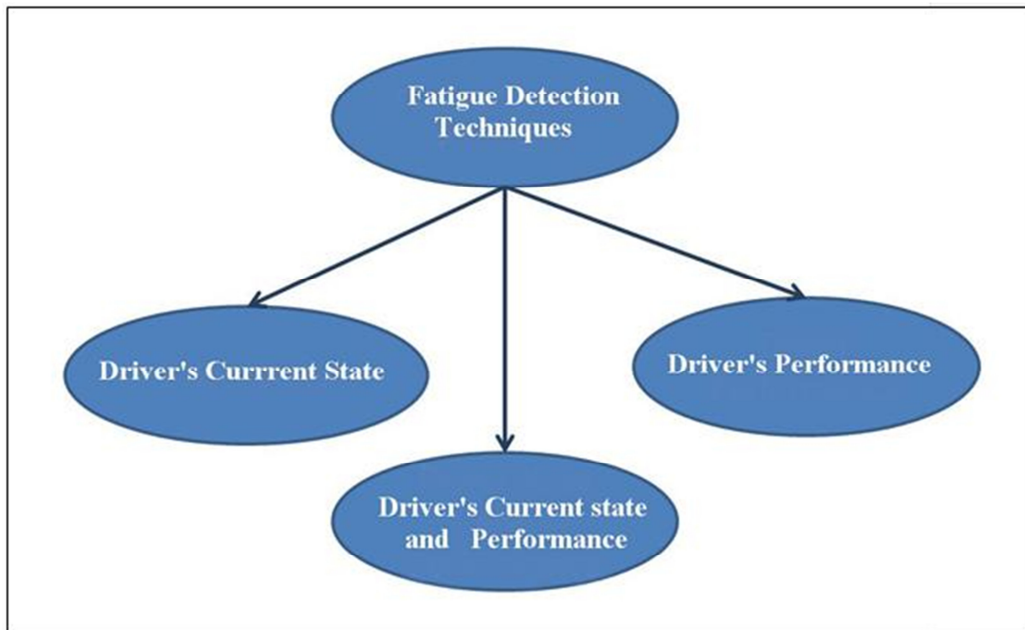


Figure 2-3: Fatigue detection technique.

2.7.1 Methods Based on Driver Performance

The techniques used to detect fatigue through driving performance are more convenient since they don't require the use of wearable or invasive sensors. Besides, many modern cars are equipped with systems that measure the driver's inputs such as the steering wheel angle and the force applied on the pedals. From our point of view, these techniques should take into consideration that the driving performance is affected by factors other than fatigue, for instance weather conditions, the driver's experience, and road conditions. These are obstacles that these methods should overcome.

The majority of the studies in this area have focused on lane tracking to detect a driver's state based on his/her driving performance, and some studies have combined this method with distance tracking of the driver's car and the car in front (Wang et al., 2006). Also, several studies were conducted to detect the driver's fatigue by analysing the movements of the steering wheel.

2.7.1.1 Steering Wheel

The approach of (Sayed & Eskandarian, 2001) of detecting fatigue through steering wheel data, has achieved satisfactory results (89.9 percent accuracy rate). Their method is based on the detection of small corrections that the driver makes on a highway, in order to keep the car in the center of the lane. The recorded data is then fed to a *Neural Network*. According to the study, this method can only be applied on straight roads. Also, it does not take into consideration the effects of various weather conditions on the driving; a driver probably drives differently when it is snowing or raining than when it is sunny.

(King, Mumford, & Siegmund, 1998) also developed an algorithm to detect fatigue by using three weighting functions in time, frequency and phase domains to quantify different steering wheel inputs. Some of the quantified inputs are the quick and sudden movements of the steering wheel, as shown in Figure 2-4, which may be corrections applied to the steering wheel because the driver was inattentive for a short time. The power spectra for the angle and the angular velocity were also used as inputs.

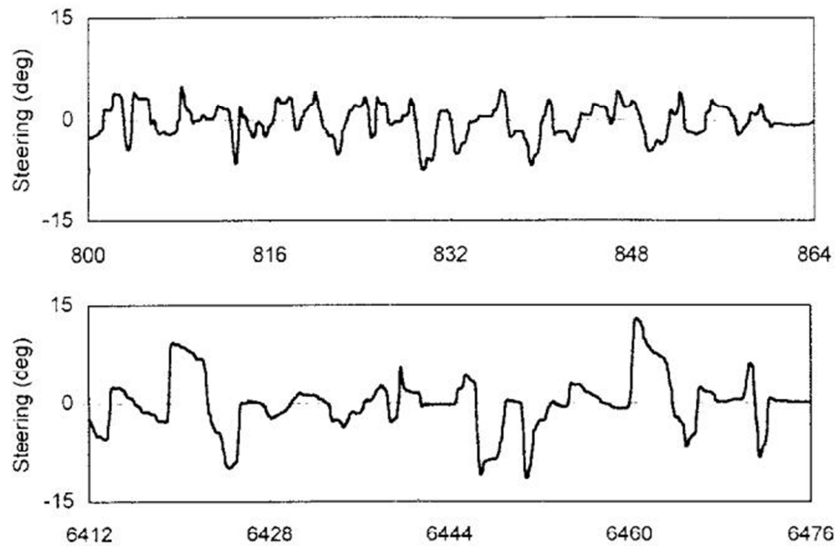


Figure 2-4: Early and late driver steering behaviour in the time domain (King et al., 1998)

(He, Li, & Fan, 2011) proposed an algorithm to compute the correlation coefficient between the lane and the steering wheel angle. The collected data was fed to a Bayesian Network model that is able to detect fatigue. According to the authors, the results of this approach were effective, achieving 79% accuracy. This model has an advantage since it is non-intrusive, but it also has some drawbacks. This system doesn't take into consideration how people vary in their manipulation of the steering wheel, or how they steer. Therefore, it is not considered an accurate system for detecting fatigue, unless it is combined with a different approach, in order to overcome its current drawbacks (He et al., 2011).

(Thiffault & Bergeron, 2003) conducted a study on the effect of the monotony of the road on fatigue. The frequency of small ($1-5^\circ$), large ($6-10^\circ$), and extreme ($>10^\circ$) steering wheel movements were recorded. The results indicated a decrease in the small movements of the steering wheel, while the large movements increased. Figure 2-5 shows that users made larger steering wheel movements on road (A). The difference between road A and B was that road A had repetitive roadside stimuli, which made it more of a monotonous road, in contrast to road B. Indeed, according to the author, the presence of large steering wheel movements might be used as an indicator of fatigue based on the empirical observations in this study.

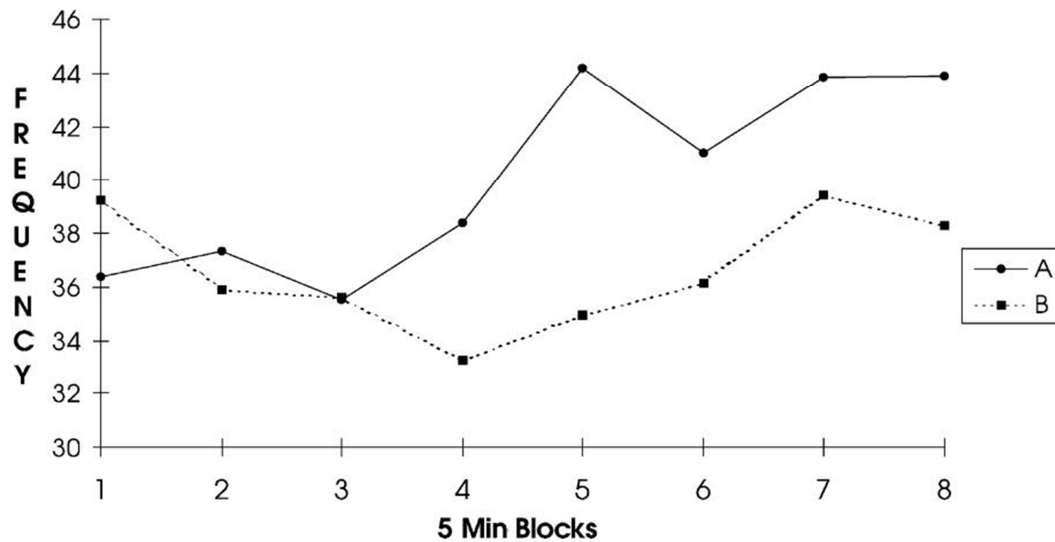


Figure 2-5: Frequency of large steering wheel movements (Thiffault & Bergeron, 2003).

2.7.1.2 Standard Deviation of Lateral Position

Lane departure is widely considered as an indicator of drowsiness, and it can be calculated as the standard deviation of lateral position of the car. The SDLP has been used by several studies such as in (ÅKERSTEDT et al., 2005) to show decrements in driving performance.

(Ingre, ÅKERstedt, Peters, Anund, & Kecklund, 2006) conducted a study and found that the SDLP increased as KSS ratings increased. For instance, KSS ratings of 1, 5, 8, and 9 corresponded to a SDLP (in meters) of .19, .26, .36, and .47, as shown in Table 2-1.

However, some drivers in the experiment rated their sleepiness at 9 in KSS, yet their SDLP did not exceed .25. Also, it has been reported that lane tracking variability increases with prolonged wakefulness.

Table 2-1: (Ingre, ÅKerstedt, Peters, Anund, & Kecklund, 2006).

<i>Parameters</i>	<i>SD of the lateral position (m)</i>		<i>Eye blink duration (s)</i>	
	<i>mean</i>	<i>SEM</i>	<i>mean</i>	<i>SEM</i>
<i>KSS levels</i>				
1	0.1911	0.0632	0.1023	0.0084
2	0.2123	0.0513	0.1109	0.0066
3	0.2211	0.0421	0.1137	0.0050
4	0.2421	0.0441	0.1184	0.0053
5	0.2615	0.0463	0.1183	0.0057
6	0.2573	0.0416	0.1190	0.0049
7	0.2774	0.0415	0.1250	0.0049
8	0.3576	0.0405	0.1402	0.0047
9	0.4654	0.0395	0.1512	0.0046
Wald test of factor	df	χ^2 (<i>P</i> -value)	df	χ^2 (<i>P</i> -value)
KSS	8	80.54 (0.000)	8	104 (0.000)
Random effects	SD	SE (<i>P</i> -value)	SD	SE (<i>P</i> -value)
Intercept	0.1008	0.0264 (0.000)	0.0096	0.0028 (0.000)
KSS	0.0669	0.0084 (0.000)	0.0098	0.0013 (0.000)
Error	0.0952	0.0035	0.0134	0.0005
Log-likelihood		323		1136

The table shows estimated means (mean), standard error of the mean (SEM) and the standard deviation (SD) with standard error (SE) of the random effects. A Wald test was used to test for significance of the KSS and a one-degree-of-freedom likelihood ratio test was used to test for significance of the random effects. The models included 10 subjects and a total of 424 observations.

(De Valck & Cluydts, 2001) conducted a study on partially sleep deprived drivers, to study the effect of 300mg of slow-release caffeine on driving performance. The lane and speed deviations decreased after taking the caffeine dose as shown in Figure 2-6. The study concluded that the lane and speed deviations were higher when drivers were sleepy.

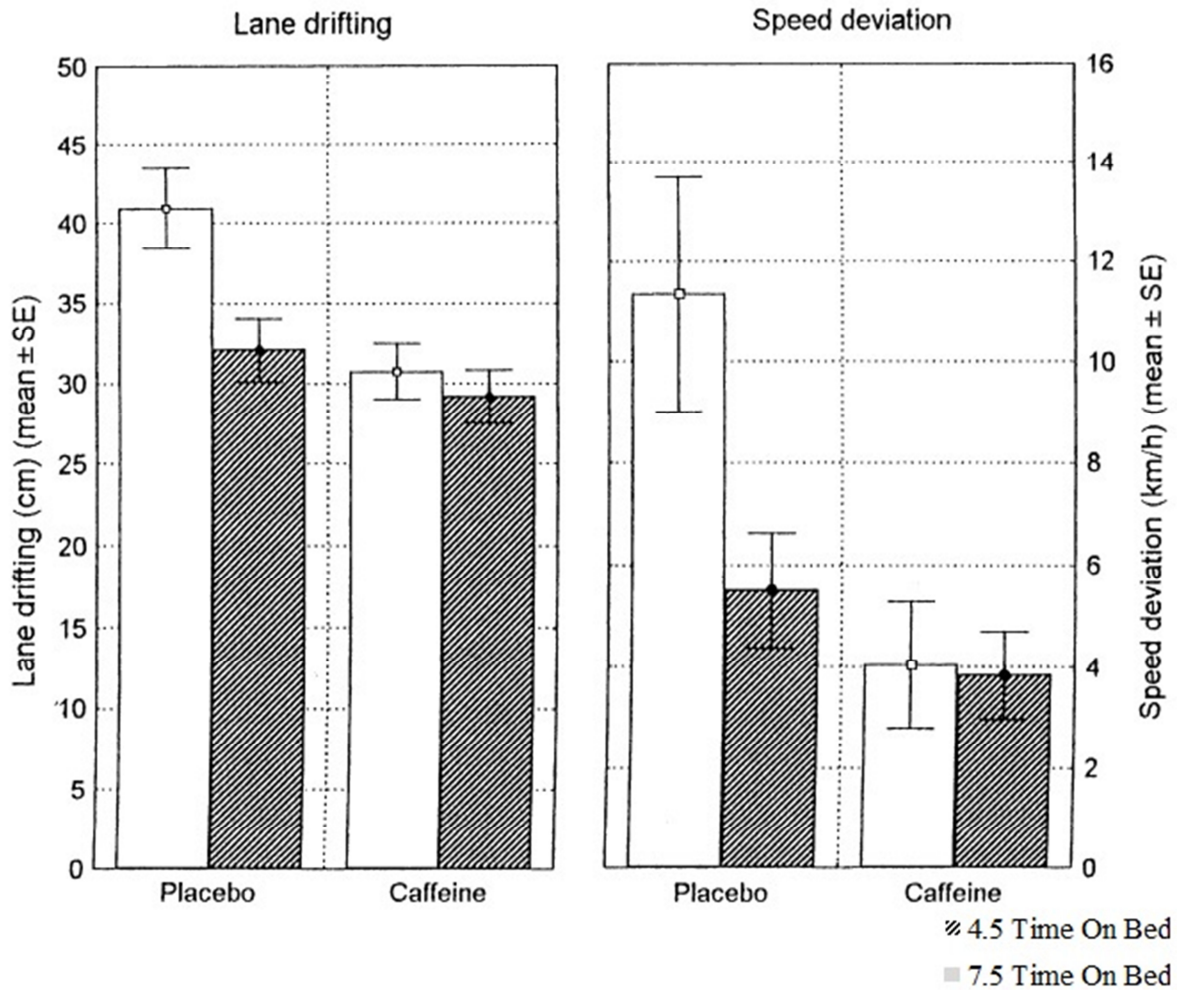


Figure 2-6: The effect of caffeine and time on bed on driving performance (De Valck & Cluydts, 2001).

(Moller et al., 2006) evaluated driving performance by tracking the car position in the lane as well with speed deviations and reaction time. The results showed a statistically significant difference between the recorded value of lane tracking in the morning and the afternoon, indicating a performance decrement when the frequency of microsleeeps was higher in the afternoon.

However, some drivers might fall asleep without changing the lateral position of the car. In other words, they might experience microsleep, and a technique that depends only on the car's lateral position might not detect that if the lateral position did not change, according to (Wang et al., 2006). Besides, the driving style differs from one driver to another, which makes it difficult to detect fatigue through SDLP since for some users it does not increase significantly, as in (Ingre, ÅKERstedt, Peters, Anund, & Kecklund, 2006).

2.7.2 Method Based on Driver's State

2.7.2.1 Eye

A driver's eye behaviour can provide reliable information about his/her alertness; therefore, capturing these behaviours can be a good indicator for fatigue (Wang et al., 2006).

In order to detect fatigue through a driver's eyes, the eyes first have to be located. Most of the research that is conducted in this area can be divided into two categories: passive appearance-based, and active IR (Infra-red) based methods. The substantial idea of the first method is that the eyes have a different appearance than the other parts of the face. In this method, one of approaches to locate the face would be used such as neural network or a technique based on skin colour based. Once the face is located, the eye region is spotted, and

then the eyes are detected by the eye windows. On the other hand, the second method, active IR, uses the bright effect of the pupil to detect the eyes. The higher contrast of the pupil compared to the other parts of the face can notably enhance eye tracking accuracy and robustness (Wang et al., 2006).

(Eriksson & Papanikotopoulos, 1997) located the eyes by locating the face in grey images, using a symmetry-based approach. The system they proposed detects whether the eyes are open or closed, by using template matching.

PERCLOSE stands for Percent Eye Closure, which is a method that detects fatigue by calculating the percentage of the total time that the driver's eyelids are closed over a specified period. If the percentage is 80% or more, the driver is most likely to be sleepy (Dinges & Grace, 1998).

However, there are some considerations that should be taken into account according to Horne and Reyner such as lights of incoming vehicles, outside lighting, air temperature and the state of the ventilation system in the car. Furthermore, drivers might not be comfortable with the use of a camera to detect their fatigue, due to privacy issue. Besides, wearing glasses may be an obstacle to detecting driver's eyes. There are, also, other considerations that have been addressed by several research studies. For instance, video instability that resulted from the vibrations of the car can be reduced by using a strategy of repeat confirmations of detected facial features in successive images (Yao et al., 2010).

2.7.2.2 EEG

The EEG is known to be a very reliable and accurate indicator of fatigue (Erwin, Volow, & Gray, 1973). EEG measures the electrical activity of the brain through electrodes placed on the scalp. This electrical activity reflects the mental state of a person as shown in Table 2-2. Therefore, the changes in the mental state such as being asleep, awake, alert or fatigued can be identified through EEG (Wilson & Fisher, 1995).

Table 2-2: EEG signal characteristics.

EEG Signals	Frequency Range	Characteristics
Delta	1-3 HZ	Deep sleep
Theta	4 – 7 HZ	NREM stage
Alpha	8 – 13 HZ	Relaxed state
Beta	>14 HZ	Active state

Delta rhythms:

Delta rhythms are slow, less than 4 Hz, and they are a sign of a deep sleep.

Theta rhythms:

Theta rhythms are about 4-7 Hz, and have greater amplitude than the other waves. These rhythms reflect different psychological states such as hypnologic imagery, and a decreased level of alertness during sleepiness.

Alpha rhythms:

Alpha rhythms are within the frequency range of 8-13 Hz, and have higher amplitude than Beta waves. These rhythms are present during a relaxed state.

Beta rhythms:

Beta rhythms are the fastest, 13-30 Hz, and have the smallest amplitude compared to the other waves. Beta rhythms indicate a state of alertness.

Sleep states can be categorized into two categories: rapid eye movement (REM) and non-rapid eye movement (NREM). The NREM stage has four stages: 1, 2, 3 and 4, according to sleep scoring standards (Rechtschaffen Kales, A., n.d.).

Normally, people slide through the four stages of the NREM stage and into the REM stage in a repetitive cycle, every hour and a half. Since the EEG is considered a reliable indicator of fatigue, it has been used by many researchers to validate and compare the results of their methods of fatigue detection, rather than as a fatigue detection method itself (Wang et al., 2006).

(Papadelis et al., 2006) concluded that EEG can effectively reflect the changes that happen a few seconds prior to sleepiness/drowsiness while driving, and the measurements of those changes can indicate potential drowsiness. (Lal, Craig, Boord, Kirkup, & Nguyen, 2003)

conducted a study to examine the psychophysiological variations as a result of fatigue. Their results show a notable increase in Delta and Theta activity when subjects are fatigued. (Lal et al., 2003) presented an EEG algorithm that is able to detect fatigue in simulated conditions. (Torsvall & Åkerstedt, 1987) conducted a study on 11 train drivers by using the EEG. The study showed an increase in low frequency EEG as a substantial sign of fatigue.

Based on several studies, EEG is considered a reliable indicator of fatigue. Yet, it is considered difficult to obtain the EEG signals in real life situations. Signal noise and especially drivers not being comfortable with the EEG sensors are considered obstacles in the implementation of this detection method in real life.

2.7.2.3 Facial Features

The analysis of facial expressions consists of three phases: detection of the region of interest such as eye or mouth, identifying the expression, and tracking the expression. (Fan et al., 2007) located and tracked the movements of the driver's mouth using a CCD camera to detect fatigue when the driver yawned. In their study, Gravity-Center was used to detect the driver's face, and Gabor wavelets were used to extract texture features from the corners of the driver's mouth. The results of the study show that Gabor Coefficients are better than geometric features to detect a driver's yawning, with a 95% average recognition rate.

In (Saradadevi & Bajaj, 2008) driver fatigue is identified by detecting a driver's yawning. Support Vector machines were used in order to detect yawning an alert fatigue.

In many previous works, there were common assumptions. These assumptions are: frontal facial views, a stable lighting source, and illumination. However, in real life, these assumptions are not always true.

An important limitation of some the physiological indicators of drowsiness is that that physiological signs of drowsiness that occur behind the wheel are different than those that appear in bed, since the driver is motivated to stay awake (HORNE & REYNER, 1996). Moreover, drivers might not be comfortable using a camera, since many people associate the idea of installing a camera with a violation of their privacy; besides, using cameras to detect driver's fatigue might not be reliable due to lighting, stability, and other issues such as wearing sunglasses. This might explain why methods that depend on the use of cameras have not been implemented by car manufactures yet, to the best of our knowledge.

2.8 Criteria of Fatigue Detection Systems Based on Driving Performance

According to (Liu, Hosking, & Lenné, 2009), vehicle-based measures should be calculated as averages over time, because these measures are not constant over time. For instance, the variables of driving performance that were acquired in different time intervals and reported in (Thiffault & Bergeron, 2003) are not constant over time. Furthermore, they concluded that shortening the time window may increase false alarms since the system would detect just noise. In contrast, a significantly longer time window may lead to missed true alarms (Kwon & Lee, 2002). Indeed, if a driver drives on the same track repeatedly, the recorded driving

data would rarely be identical. Therefore, it should be calculated as averages over time, which is what we have considered in our approach as well as the maximum. Moreover, the accuracy of the system would decrease if the time window is too short or long. A two minutes time window that we considered has been suitable for our experiment that was conducted on a 3D driving game. In the driving game, users could finish the track within few minutes. Therefore, the track is considered to be significantly smaller than real life. As a result, the size of time window could be carefully increased in real life since over increasing may decrease the accuracy of the system.

Fatigue detection techniques that are based on a driver's behaviour need to address the issue of individual differences. (Brookhuis, De Waard, & Fairclough, 2003) shed some light on this issue by referring to differences between absolute and relative criteria. In the former, the criteria can be applied to all drivers, whereas the latter can only be applied to some drivers. According to (Liu et al., 2009), individual differences were overlooked in some studies because they used the averages from all drivers. For example, in (Ingre, Åkerstedt, Peters, Anund, & Kecklund, 2006) the results of each driver were presented, therefore displaying the differences in their driving performances. Indeed, individual differences are not only present in techniques that are based on driver's performance, but also in techniques that are based on physiological signs. For instance, individual differences are present in EEG (Cacioppo & Tassinary, 1990). To overcome the issue of individual differences we consider personalized Bayesian Network (PBN). In order to demonstrate the effect of this issue on the accuracy of

the system, we will compare the results of the (PBN) to a not-personalized Bayesian Network in Chapter 5.

In addition, using multiple sensors or measures to detect a driver's level of fatigue may increase the accuracy of the system, as well as its reliability. Indeed, using a single measure or sensor to detect a driver's drowsiness may be unreliable in some situations (Renner & Mehring, 1997). For example, wearing sunglasses may prevent the success of the techniques that detect fatigue through eye movements.

Chapter 3 Bayesian Network

This chapter provides a brief overview of Bayesian Network and its advantages including an example of BN.

3.1 Definition

A Bayesian Network (BN) represents joint probability distribution and domain knowledge using a graphical diagram that contains variables, called nodes, and arrows linking these nodes, which represent the relationships or independency among these variables.

(Pearl, 1986) explained the principles of BNs and how links between variables can be quantified with conditional probabilities. BNs have the ability to reason under uncertainty (Nielsen & JENSEN, 2007). BNs can effectively provide a method for representing the knowledge about uncertain variables by combining prior knowledge with the observed data. BNs also have the ability to utilize expert knowledge, which is beneficial when there is missing or limited data about a variable, or when the domain itself is very complicated (Nielsen & JENSEN, 2007; Pearl, 1986).

3.2 Why a Bayesian Network

According to (Ji, Lan, & Looney, 2006), fatigue detection process faces several challenges. For instance, the phenomenon of being fatigued is not directly observable. Yet, fatigue can be detected through its signs, for example yawning. Also, some fatigue signs differ from one

person to another, depending on age, health, and other factors. Therefore, sensory observation might be incomplete or uncertain. For these reasons, the complexity of accurately detecting fatigue may require the use of probabilistic methods, evidential reasoning, neural networks, and fuzzy theories. (Ji et al., 2006) concluded that BN advances the other methods due to a better ability to manage uncertainty, capture dependency among network variables, and deploy prior knowledge.

(Jayasurya et al., 2010) conducted a study to compare BN accuracy to the Support Vector Machine (SVM) in predicting two-year survival in non-small cell lung cancer. Both BN and SVM were trained on 322 inoperable non-small cell lung cancer patients. The study concluded that the BN network is as accurate as the SVM. Yet, BN accuracy is better than that of the SVM when the tested data set had missing values. Therefore, according to the study, BN is more efficient for use in the field of medicine since it involves missing data.

Furthermore, (Heckerman, 2008) summarized the benefits of BN starting with its ability to handle incomplete data sets. Another benefit is its ability to learn about causal relationships. Indeed, this ability could be helpful in understanding a problem domain. Also, BNs have the ability to incorporate prior knowledge and data as well as the ability to avoid the over fitting of data.

The aforementioned abilities would allow BN to overcome the obstacles caused by the differences among drivers, when detecting fatigue. In other words, drivers have different

styles of driving, and even the same driver changes his/her driving style according to weather or traffic conditions. Therefore, with its ability to learn and manage uncertainty, BN can adapt to such differences and accurately detect fatigue.

3.3 Uncertainties

Uncertainty has been described by Dr. Hubbard as: “the lack of certainty, a state of having limited knowledge that makes it nearly impossible to predict the exact outcome”. The importance of probabilistic systems rose with the fact that logical systems or rule based expert systems could not predict or take into consideration all the possible events. For example, smoke indicates fire, but that is not always true. Indeed, the existence of uncertainty in both the professional and scientific world has led scholars to design methods or tools to address this issue as event dependent. One of the most effective methods of dealing with uncertainty is using probabilistic systems. Bayesian Network presents the probability as the degree of belief that the hypothesis is true. Moreover, BN can update the degree of belief with the arrival of new information or data.

3.3.1 Parameters Learning

An Expectation Maximization (EM) algorithm was used in the learning parameters process. EM algorithm is considered to be effective in the learning process when the training data set has missing values. The algorithm has two steps: Expectation and Maximization, used to calculate the maximum likelihood estimates of the parameters. In the Expectation step, the

missing values are assumed based on the expectations of the random variables, conditional on the observed data. In the Maximization step, a new estimate for the missing value is assigned by computing the expectation of conditional log likelihood of the complete data with respect to posteriors of the missing/hidden variable and maximizing it. The process is then repeated. As a result, the log likelihood value will increase after each repetition. This process of repetition will stop if the difference between the log likelihood of two consecutive repetitions is sufficiently small.

3.4 Inference

After the learning phase, the BN is able to answer probabilistic queries on variables in the network. Calculating the posterior of a node after entering the evidence, the value of the remaining nodes, is called probabilistic inference. The node of interest in our network is Fatigue. Therefore, the inference was performed on this node.

3.5 Example of Bayesian Network

Wet grass is one of the famous examples for the use of BN (Alpaydin, 2004). In this example, the grass is wet either by rain or by a sprinkler. Applying BN to this case enables us to know the probability that the sprinkler was on, that it rained, or that the grass is wet. First, we create a Directed Acyclic Graph (DAG) of this network as shown in Figure 3-1.

The DAG consists of nodes and arcs between them that represent the conditional independency.

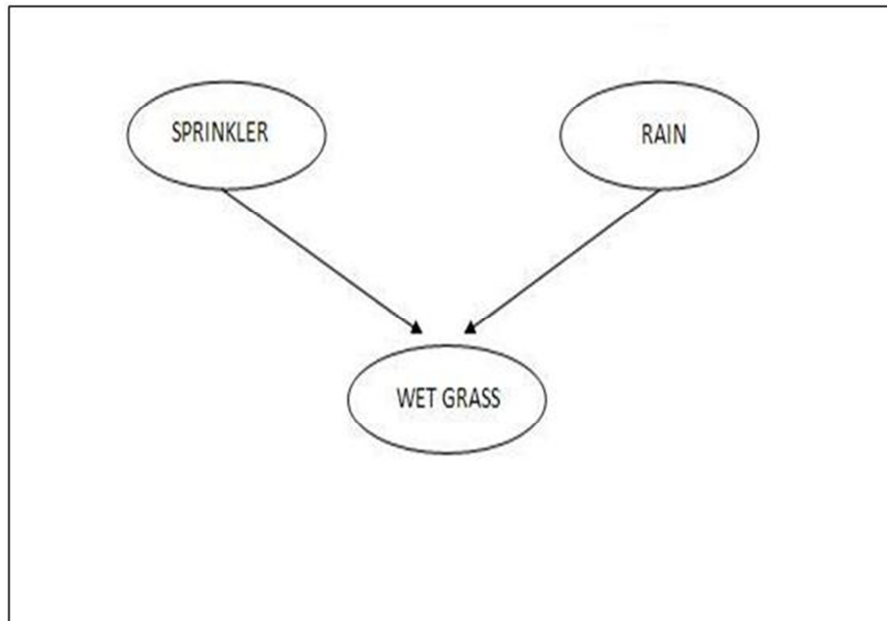


Figure 3-1: DAG wet grass.

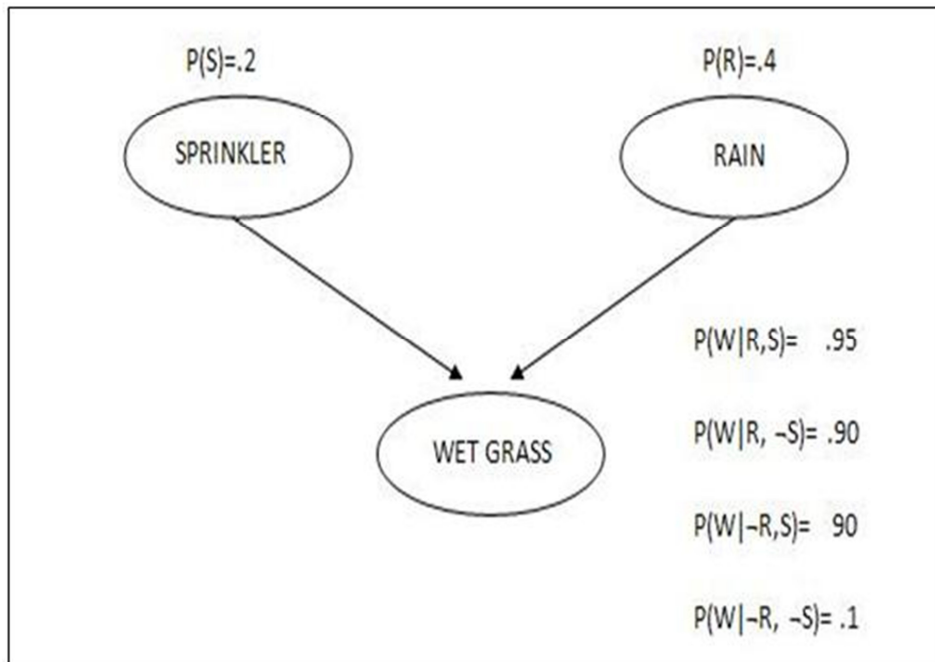


Figure 3-2: The conditional independency of the nodes in DAG of wet grass.

As shown in Figure 3-2, we have three nodes: Sprinkler, Rain, and Wet grass, as well as arcs between them that show the cause and effect relationship. We know that rain causes the grass to be wet and not the opposite. In this example, we know that it rains on 40% of the days in the year, and that the probability of the grass getting completely wet on one of these rainy days is 90%, while 10% of the time the grass will not get completely wet as the rainfall is too little. Also, there is a 20% chance that the grass will be wet on a non-rainy day, because the sprinkler.

Since it rains on 40% of the days of the year, we know that 60% of the time it does not, $P(\neg R) = .6$. Furthermore, there is a 10% chance that the grass will not be completely wet when it rains, $P(\neg W|R) = .1$. Also, the probability of the grass not being wet since it did not rain is 80%, $P(\neg W|\neg R) = .8$.

Given that the grass is wet, we can use Baye's rule, $P(R|W)$, to know if it rained or not, as in 3.1.

$$P(R|W) = \frac{P(W|R) P(R)}{P(W)} \quad (3.1)$$

,

where $P(W)$ is the probability that the grass is wet, either because of the rain or not, and can be obtained by equation 3.2.

$$P(W) = P(W|R) P(R) + P(W|\neg R) P(\neg R) \quad (3.2)$$

Therefore,

$$P(R|W) = \frac{P(W|R) P(R)}{P(W|R) P(R) + P(W|\neg R) P(\neg R)} \quad (3.3)$$

$$P(R|W) = \frac{.9 \times .4}{.9 \times .4 + .2 \times .6} = .75 \quad (3.4)$$

We know that the probability of the grass being wet if it rains is 90%, yet we do not know the probability of the grass being wet if the sprinkler is on. Therefore, we can also use Baye's rule to infer the probability of the grass being wet because of the sprinkler by equation 3.5.

$$P(W|S) = P(W|R, S) P(R, S) + P(W|\neg R, \neg S) P(\neg R, \neg S) \quad (3.5)$$

Since the nodes "Sprinkler" and "Rain" are independent in this graph, $P(R|S) = P(R)$.

Therefore,

$$P(W|S) = P(W|R, S) P(R) + P(W|\neg R, \neg S) P(\neg R) \quad (3.5)$$

$$P(W|S) = .95 \times .4 + .9 \times .6 = .92 \quad (3.5)$$

Chapter 4 Proposed System

According to Renner and Mehring (1997), it is not sufficient to detect fatigue based on driving performance using a single parameter. Therefore, in order to detect fatigue through driving performance, we collect data from several sources. Furthermore, we include some contextual data that have effects on fatigue or driving performance. Also, driving style differs from a driver to another, and even for the same driver it would differ depending on driver's mood, traffic and environment conditions. Therefore, using multiple parameters such as steering wheel, pedals, and grip force may reflect driving performance more accurately than using only one of them.

4.1 Requirements

In order to detect fatigue accurately, the system need to address the following factors:

- 1- The system should detect fatigue accurately.
- 2- The system should avoid using any intrusive or wearable sensors when it is possible.
- 3- The system should be context aware since driving performance differs depending on weather and traffic.

In order to detect fatigue through driving performance, the system should use data that reflects the driving performance, such as the data from the steering wheel and the pedals, and

the system should overcome the issue of individual differences since users have different driving styles.

4.2 Architecture Overview

We propose a personalized Bayesian Network to detect driver's fatigue. The main goal of our approach is to detect fatigue accurately without using intrusive or wearable sensors.

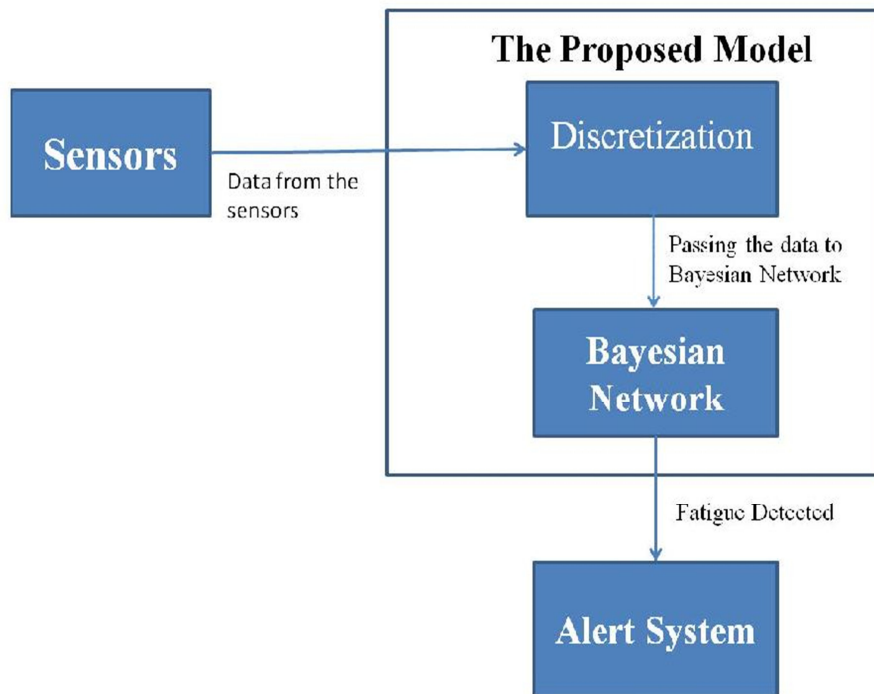


Figure 4-1: An overview of the system architecture.

The system uses data that can be acquired from modern cars such as the steering wheel angle and the pressure applied to the pedals. Also, it is context aware and can therefore work under various conditions. Moreover, the system consistently reads the data from the steering wheel,

pedals, and pressure sensors every 0.1 seconds, and every two minutes the system detects fatigue through the collected data after the discretization process. Figure 4-1 shows the system architecture which can be summarized as follows: after passing data from the sensors, the data will be discretized. Then, Bayesian Network will detect fatigue, and when fatigue is detected the alert system may be provoked. Also, whether fatigue is detected or not, the system will continue to seek fatigue every two minutes.

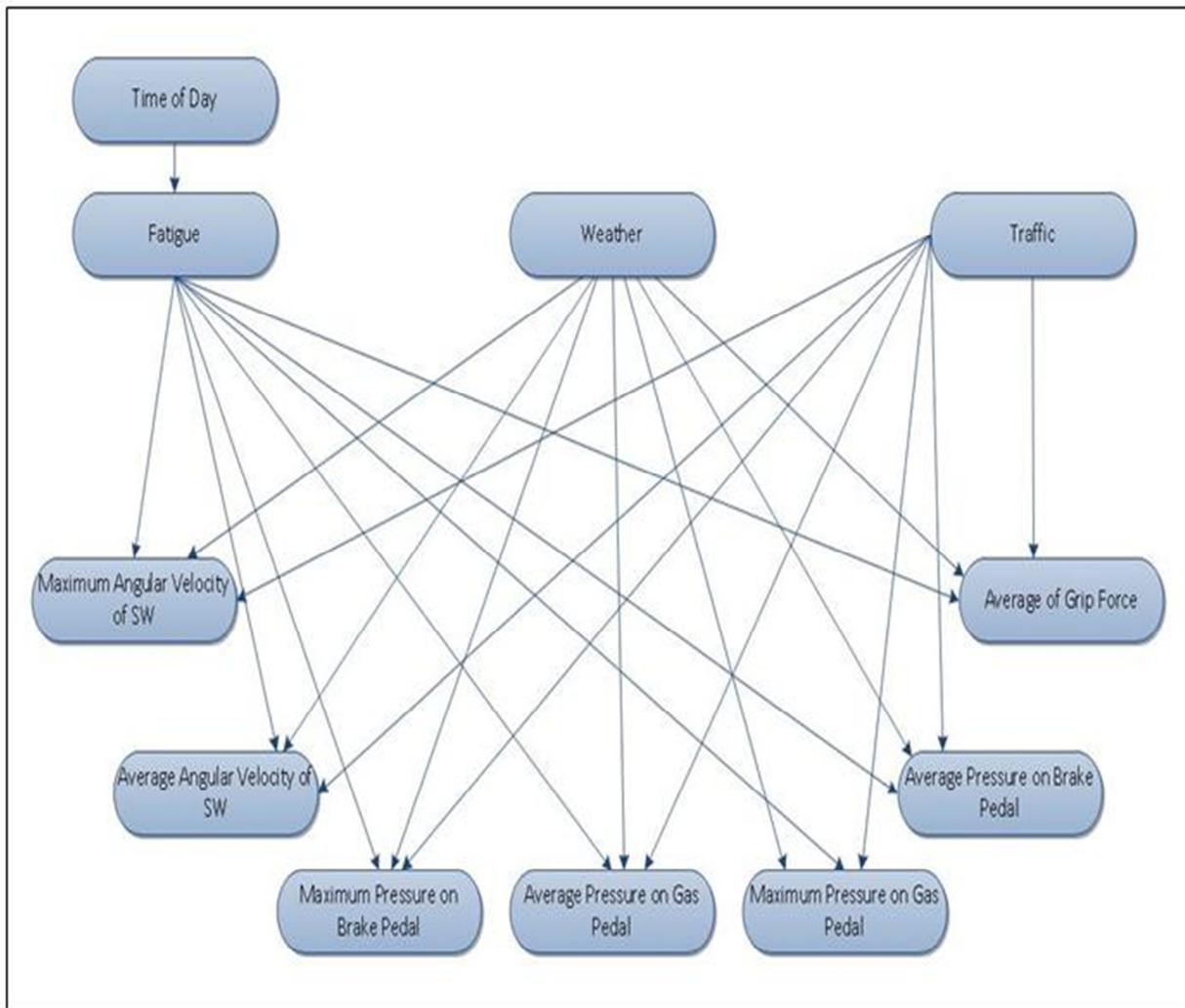


Figure 4-2: DAG of the proposed system.

Figure 4-2 shows the DAG of our BN. As can be seen, the weather affects the driving performance. For example, driving in sunny weather differs from driving in snow. Different weather conditions require different styles of driving. In snowy weather, drivers may experience some sliding or drifting that makes them steer hard or consistently in different directions, in order to control the car. The effects of various traffic conditions are also reflected on the driving performance. For instance, driving in heavy traffic requires the driver to use the brake more than usual, since he/she needs to stop repeatedly. Furthermore, as seen in the literature review, fatigue causes the driver's performance to deteriorate. Also, the performance of the driver differs depending on whether the driver is alert or fatigued, as will be shown in the next chapter. Therefore, the "Weather", "Traffic", and "Fatigue" nodes affect the following nodes in our network: "The maximum angular velocity of the steering wheel", "The average angular velocity of the steering wheel", "The maximum gas pedal pressure", "The average gas pedal pressure", "The maximum brake pedal pressure", "The average brake pedal pressure", "The average grip force".

Moreover, as indicated by several studies, fatigue is affected by the time of day. There are two sleep peaks in the day, which are in the mid-afternoon and in the early morning. Hence, the node "Time of Day" affects the node "Fatigue".

4.3 PBN Parameters

The main goal of a BN is inferring the unobserved event from the observed data. In our Personalized Bayesian Network, fatigue is what we intend to infer from the information available. There are many factors that contribute to fatigue, as well as to its symptoms. We used several parameters to obtain the information, but we believe these parameters can be easily acquired in modern cars since most modern cars have computing facilities controlling their functions. Also, they do not require intrusive or wearable sensors.

In order to detect fatigue through driving performance, we collect data from the steering wheel, the pedals, and the pressure sensor. Furthermore, we include contextual data that has been proven by several studies to affect fatigue and/or the driving performance. Indeed, it is not sufficient to detect a driver's fatigue based on driving performance through a single parameter. (Renner & Mehring, 1997) state that: "With ongoing research it became evident that lane departure warning and lane position parameters reflect only one facet of the performance decrements within fatigued drivers. A fatigued driver can actually keep his vehicle perfectly in the lane, provided the vehicle heading is coincidentally appropriate for the road curvature ahead. In our studies we found evidence for intentional short nap on straight road sections, on which the vehicle path was perfect, but the driver was incapable to react upon any unexpected event (e.g. front end collision). In order to prevent these dangerous situations of good lateral control without reaction readiness, a more complex drowsiness detection technique had to be developed."

Moreover, driving styles differ from a driver to another, and even for the same driver, depending on driving and environmental conditions. Therefore, using multiple parameters such as the steering wheel, the pedals, and the grip force may reflect the driving performance more accurately than using only one of them.

4.3.1 Maximum Angular Velocity of the Steering Wheel

Fatigued drivers have a slower response time and a decreased level of attention. Therefore, recording the maximum angular velocity enables us to detect a driver's sudden movements, which usually occur as a result of fatigue and not paying attention to the road and the environment. The angular velocity is calculated using the equation 4.1.

(4.1)

$$\text{Angular velocity} = \frac{\Delta x}{\Delta t}$$

Where x is the angle and t is the time.

4.3.2 Average Angular Velocity of the Steering Wheel

Several studies were conducted to detect fatigue using the steering wheel. (Sayed & Eskandarian, 2001) detected fatigue with the steering wheel by detecting the small corrections that drivers applied to the steering wheel. (Takei & Furukawa, 2005) applied the Chaos theory on the data of the steering wheel angle signals, processed by fast fourier transform, in order to detect the changes of the steering wheel motions.

To keep the car in lane, the driver generally has to keep adjusting the steering wheel. As the driver becomes fatigued, these small corrections start to diminish. Depending on the severity of the fatigue, the driver may eventually run off the road, or go off lane. In the latter, when the driver notices that he/she is going off lane, the driver usually would apply a strong movement to the steering wheel to get back in lane; this may be considered as a sudden movement due to fatigue.

4.3.3 Maximum Pressure Applied to the Gas Pedal

In our experiment, this parameter may not have a significant effect. The pedals used in our simulation were different than those used in real life, in terms of size and resistance. Also, the acceleration in the 3D simulation game is different. It was noticed that users often pushed the gas pedal to the maximum when they wanted to accelerate; this happened at least once in every two minute period. Thus, the values of this node were the maximum in most of the cases, for each user. In other words, this parameter might not have a significant effect in the experiment due to the fact that the experiment was conducted in a driving simulator. It should be noted, however, that this parameter may be beneficial in real life since it is considered to be a factor that reflects driving performance.

4.3.4 Average Pressure Applied to the Gas Pedal

Drivers adhere to the speed limits assigned to the roads. In order to maintain speed, drivers keep adjusting the pressure applied to the gas pedals. Similarly to the small corrections applied to the steering wheel, the minor adjustments to the gas pedal would be reduced as the driver becomes fatigued, which could be a factor that explains the association of excessive speed with sleep related accidents. (De Valck & Cluydts, 2001) calculated the speed deviation (i.e. the mean of the differences in km/h of the speed of the car with the assigned speed limit), and found it higher in fatigued drivers.

4.3.5 Maximum Pressure Applied to the Brake Pedal

The maximum pressure applied to the Brake pedal might indicate a sudden movement from the driver, due to inattentiveness. Alert drivers pay attention to the road and the signs. Indeed, fatigued drivers may misjudge the required distance for stopping, or overlook road signs or other objects. Consequently, fatigued drivers may apply more force brake than they usually would.

4.3.6 Average Pressure Applied to the Brake Pedal

Drivers use the brake pedal in many situations, such as when correcting their speed if it exceeded the limit, or slowing down to keep a safe distance from the vehicle in front. A

fatigued driver has slow reaction time and lack of attentiveness to the environment and the other vehicles, which can be reflected on the average pressure applied to the brake pedal.

4.3.7 Grip Force

A driver's grip force generally starts to diminish as a result of the muscles becoming relaxed due to fatigue. A decrease in the grip force could reflect fatigue (Chieh, Mustafa, Hussain, Zahedi, & Majlis, 2003). Also, fatigued drivers tend to change the way they grip the steering wheel. For instance, some drivers may change the position of their hands when they are fatigued. Becoming more relaxed due to fatigue might be associated with some involuntary movements of the drivers. Therefore, placing pressure sensor all over the steering wheel enables us to detect fatigue by capturing those changes. Indeed, those changes might be complex to interpret since drivers have different styles in handling the steering wheel. Using a personalized BN may handle such uncertainties and learn the driving style of the driver.

4.3.8 Time of Day

There are two sleep peaks in a day, which occur in the early morning and in the mid-afternoon (J A Horne & Reyner, 1995; Lenné, Triggs, & Redman, 1997; Pack et al., 1995). Several studies have shown that the performance of drivers would be impaired around these times, and they would have slower reaction time (Dinges, 2009; Mitler et al., 1997).

4.3.9 Weather and Traffic

As the driving performance is affected by fatigue, it is also affected by traffic and weather conditions. The system takes into consideration the effects of various weather conditions on the driving; a driver probably drives differently when it is snowing or raining than when it is sunny. Driving performance is also affected by traffic conditions. Therefore, including this information in the network would increase its accuracy.

Chapter 5 Experiment Setup

This chapter starts by providing details on the apparatus and software that were used in conducting the experiment as well as the Karolinska Sleepiness Scale and its validity. This chapter also explains how the experiment is conducted.

5.1 Apparatus

Several devices were used to set up the experiment as shown in Figure 5-1. A “Super Sports 3X” steering wheel that comes with pedals was used to simulate the driving experience. The *SuperSports3X Racing Wheel* continuously provides information about the state of the steering wheel and pedals. We also used a two-wire Force Sensing Resistor that is designed to be used in human touch control of electric devices and robotics applications. Its sensor has a thick polymer film that shows a decrease in resistance with increases in the pressure applied on its surface. The force sensing resistor is connected to an Arduino microcontroller board. The microcontroller has been programmed to give readings every 0.1 seconds.

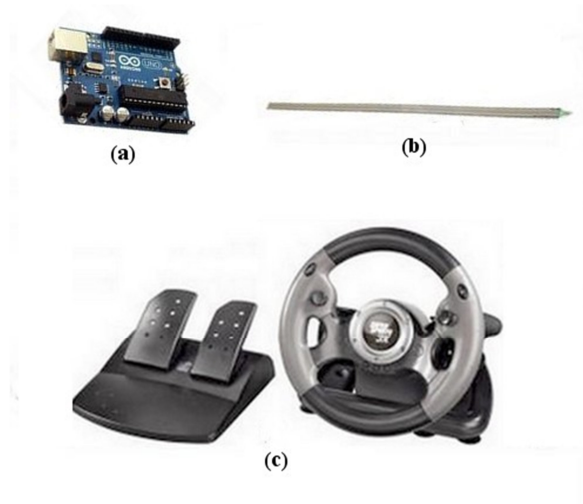


Figure 5-1: (a): Arduino microcontroller board. (b): Force sensing sensor. (c) Super Sports 3X.

5.2 Software

In order to collect the readings from the steering wheel and microcontroller, an application was designed using VB.net. The steering wheel can rotate up to 90 degrees, either left or right. The steering wheel continuously provides information about its current angle. Similarly, the pedals provide information on how much they are pushed, which is referred to as the amount of pressure applied to them. Having this information makes calculating the angular velocity of the steering wheel and the pressure applied to the pedal feasible. Moreover, as shown in Figure 5-2, a 3D driving simulator game, Driving Simulator 2011, was used for the experiment as shown in Figure 11. Finally, the data was fed to a Bayesian Network that was created by using Netica 4.16.



Figure 5-2: A screenshot of the 3D driving simulator game.

5.3 Karolinska Sleeping Scale

Karolinska Sleepiness Scale (KSS) is a subjective sleepiness scale (Åkerstedt & Gillberg, 1990). The 9 scores of KSS ranges from 1=very alert to 9=very sleepy as shown in Table 5-1. Depending on the level of sleepiness, users rate their sleepiness level by choosing one of the KSS scores.

We used the KSS to compare the results in our study. Indeed, KSS is one of the most commonly used subjective sleepiness scales, and it has been validated by several studies. For instance, (Ingre, ÅKerstedt, Peters, Anund, & Kecklund, 2006) have demonstrated a relationship between KSS, blink duration, and a standard deviation of the lateral position. A

prolonged blink duration and a higher standard deviation of the lateral position are associated with a higher KSS level, 5-9 in KSS.

Also, (Gillberg et al., 1994) provided evidence for the validity of KSS by authenticating KSS with the performance of laboratory tasks such as visual vigilance and single reaction time tasks. The experiment was conducted at night-time, and showed that the performance decreased with an increasing tendency to sleep, as reflected by KSS.

Table 5-1: KSS.

Level	Description	<input checked="" type="checkbox"/>
1	Extremely alert	<input type="checkbox"/>
2	Very alert	<input type="checkbox"/>
3	Alert	<input type="checkbox"/>
4	Rather alert	<input type="checkbox"/>
5	Neither alert or sleepy	<input type="checkbox"/>
6	Some signs of sleepiness	<input type="checkbox"/>
7	Sleepy but no effort to keep awake	<input type="checkbox"/>
8	Sleepy, some effort to stay awake	<input type="checkbox"/>
9	Very sleepy, great effort to keep awake, fighting sleep	<input type="checkbox"/>

Moreover, (Kaida et al., 2006) validated the KSS against EEG, and showed a high correlation between them. With higher KSS ratings, the number of lapses, the median reaction time, and Alpha and Theta power density showed remarkable increases.

(Kaida, ÅKERSTEDT, KECKLUND, Nilsson, & Axelsson, 2007) conducted an experiment to predict performance errors using KSS, EEG, and heart rate variability. The results showed that these indicators have a significant correlation with the performance on a vigilance task, and can therefore be used to predict performance errors.

(HORNE & REYNER, 1996) asked users to rate their sleepiness level in KSS every 200 seconds during the driving task. They found that a level 6 in KSS was associated with a minor lane departure, a departure that did not occur when the level of KSS was lower.

(Ingre, ÅKERstedt, Peters, Anund, Kecklund, et al., 2006) asked the drivers to score their sleepiness level in KSS every 5 minutes, and estimated that the risk of major lane departures for the average driver increased by 185 times if sleepiness increased from 5 to 9 in KSS, with respect to individual differences.

5.4 Experiment Hypothesis

T In this experiment, our working hypothesis is to accurately detect driver's fatigue through Bayesian Network without using intrusive or wearable sensors. Most of the used parameters in the model can feasibly be acquired in modern cars. Moreover, drivers have different driving style, which may be an obstacle in detecting fatigue accurately through driving performance. Yet, BN has the ability to learn as well as the ability to manage uncertainties. Therefore, the system should overcome this issue and detect fatigue accurately.

5.5 Experiment Protocol

The users were asked to drive for few minutes to be familiar with the driving simulator. The track in the games has some curves and straight segments of road; also it has one traffic light. The total time of driving was one hour divided into six sessions, each session is 10 minutes long. The users were asked to drive for three sessions while they are fatigued. There are approximately two sleep peaks in the day, in afternoon and early morning (J A Horne & Reyner, 1995; Lenné et al., 1997; Pack et al., 1995). Therefore, users were asked to drive three sessions at these times. At these times, the likelihood of users being fatigued would be high due to circadian rhythms. Moreover, most users come to the lab in the morning; therefore, they would probably be tired from working around 3-5 P.M. Also, the monotony of driving games may be a factor in elevating process of being fatigued. The other sessions were at times where users would probably be fully awake and not tired. The track and driving conditions were the same for all the users. Users were asked to maintain a specific speed limit that is suitable for the simulated road, and respect the traffic rules. After each session, the users were asked to rate their level of sleepiness using Karolinska Sleepiness Scale (KSS), which is mentioned earlier in Section 5.3.

5.6 Data Collection and Discretization

While the user is driving, the data from the steering wheel, the pedals, and the pressure sensor is collected every 0.1 seconds, in order to calculate the maximum value and the average value, every two minutes. The periods of time of acquiring data and making decision

might be changed. Yet, reading data with long interval time between readings might result in missing some important readings or driver's reactions. In contrast, long interval times may decrease the reliability of the system to detect fatigue before accident happen. Furthermore, making decision with short interval times may increase false alarms. In our experiment, the driving session was ten minutes long. Therefore, we have five cases in each session since we make a decision in every two minutes. Eventually, six sessions for each user generated 30 cases sufficient enough to perform the learning process.

The system records the following data:

- The maximum angular velocity of the steering wheel.
- The average angular velocity of the steering wheel.
- The maximum pressure applied to the gas pedal.
- The average pressure applied to the gas pedal.
- The maximum pressure applied to the brake pedal.
- The average pressure applied to the brake pedal.
- The average pressure applied on the force sensing sensor.
- The weather information.
- The traffic information.
- The time of day.

Once the data is collected, it is discretized and then fed to BN. Indeed, all the nodes in our BN are discrete, which means they have discrete values. Each node has a limited number of states or values. For instance, the maximum and average angular velocity nodes of the

steering wheel have five states, as well as the average of grip force. Also, the nodes for the average pressure applied to the gas and brake pedals have five states. However, the nodes for the maximum amount of pressure applied to the gas and brake pedals only have three states, since the maximum values are fixed at 99 by the factory.

On the other hand, the nodes for traffic, weather, time of the day, and fatigue have two states. Based on our experiment and the limited data we had, we found that the number of states for these nodes was appropriate for the experiment. However, if the data is not discretized, the nodes will have a larger number of states. Consequently, with the limited data we have, that will result in a large number of missing data and would significantly decrease the accuracy of the system. For example, the maximum pressure applied to the gas pedal ranges from 0 to 99. Without discretization, this node would have 100 states instead of only three states. As result, the system would have a vast amount of missing data, to the point where it could not make a prediction. Besides, there is no significant difference if the pressure applied to the pedal was 60 or 61. For these reasons, we confined the number of states for this node to three states. Then, we fit the value acquired from the sensor into one of these states, by using the following equation:

$$(\text{Highest value recorded} - \text{Lowest value recorded}) / \text{number of states}$$

We can set a range of values for each state, and assign a state to the node based on the value acquired from the sensor.

Moreover, the discretization process is done separately for each user, in order to optimize the output of the network, with the limited data we acquired

Chapter 6 Analysis of the Data and Testing

This chapter shows the analysis of the data acquired from the steering wheel, pedals and pressure sensor. The data demonstrates the issue of individual differences among drivers, which support our approach of using a Personalized Bayesian Network. Also, this chapter provides detail about testing the system and its accuracy. Furthermore, the result of the Personalized Bayesian Network is compared to a non-personalized Bayesian Network in order to demonstrate the effect of individual differences on the accuracy.

6.1 Analysis of the Data

6.1.1 Steering Wheel

The data collected from the steering wheel can reflect the driver's state. The differences between how a driver steers while alert or fatigued is reflected in the data. The recorded maximum angular velocity might reflect the sudden movements made by the driver.

Based on our observation, fatigued users more often go off lane, and keep steering widely to stay in lane. Also, they tend to have difficulty driving straight for a long distance without the car swinging/weaving. Moreover, in the survey of Ontario police officers conducted by TIRF, 84.2% of police officers consider frequent lane changing/weaving as a sign, among

other things such as wide steering, of a fatigued driver (Traffic Injury Research Foundation, n.d.).

For most of the users, the values of the maximum steering wheel angular velocity recorded were higher when users were fatigued as shown in Table 6-1, and reached its highest value when driving under that condition. Fatigued driving may be categorized by a prolonged reaction time and a decrease in the level of attention. As a result, a fatigued driver would usually be in a situation that requires fast steering to avoid something or to get back to the lane. In other words, the maximum angular velocity of the steering wheel may indicate sudden movements, which would be a result of fatigued driving. Also, Figure 6-1 and Figure 6-2 show some differences among users.

Table 6-1: Average maximum angular velocity (degree/second).

Users	Alert	Fatigued
1	125	109
2	99	127
3	129	95
4	191	172
5	67	124
6	53	82
7	91	98

8	138	171
Total	893	977
Total Average	112	122

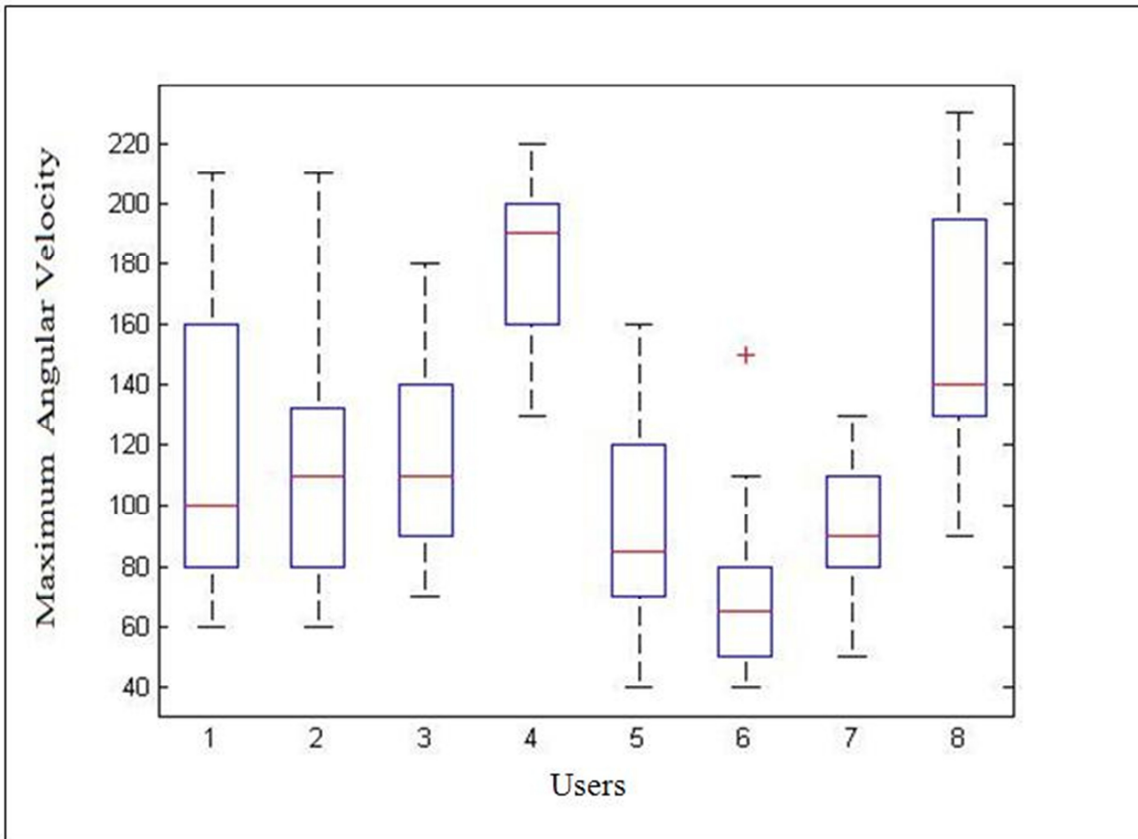


Figure 6-1: Maximum angular velocity (degree/second).

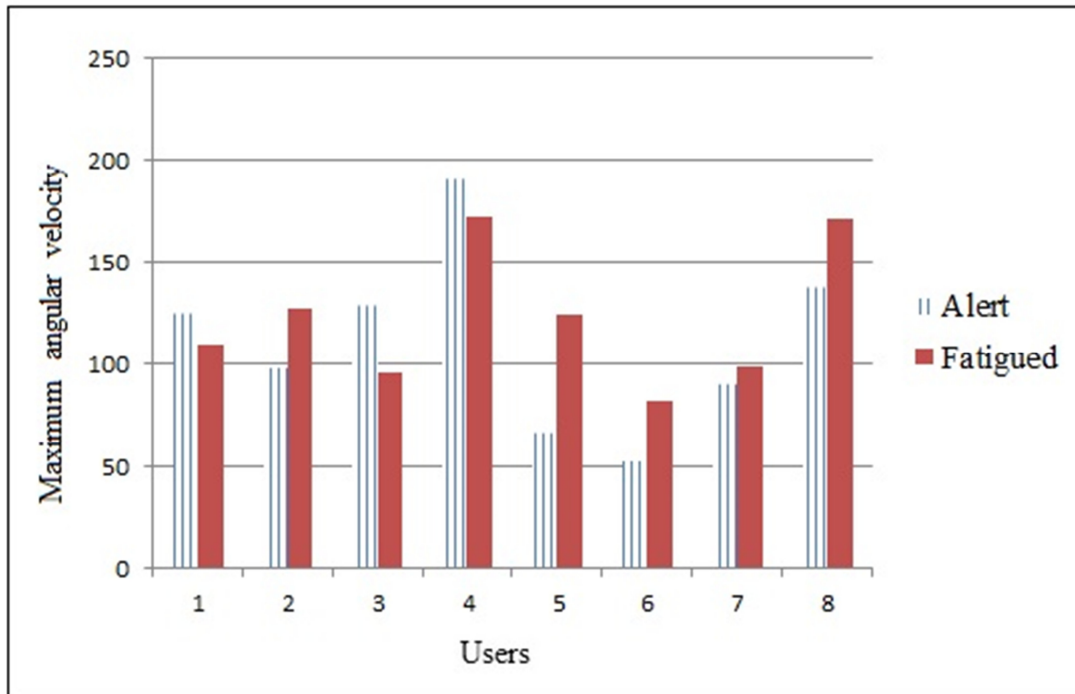


Figure 6-2: Maximum angular velocity

Moreover, as shown in Table 6-2, the average angular velocity shows some changes according to a driver's state. Those changes depend on the driver's personality and other factors such as the level of familiarity or expertise with driving games, since the experiment was conducted using a 3D driving game, and the reduction of small corrections that the driver applies to the steering wheel to keep the car in the lane. Indeed, as it has been observed that fatigued drivers generally could not stay in one lane and kept changing lanes, especially in curves. Yet, other drivers did not show a significant difference in these instances as shown in Figure 6-3 and Figure 6-4.

Table 6-2: Average angular velocity (degree/second).

User	Alert	Fatigued
1	8.94	6.97
2	5.40	5.48
3	10.85	7.01
4	9.31	9.28
5	4.47	5.83
6	2.96	4.90
7	4.48	4.63
8	7.74	8.45
Total	54.15	52.55
Total average	6.77	6.57

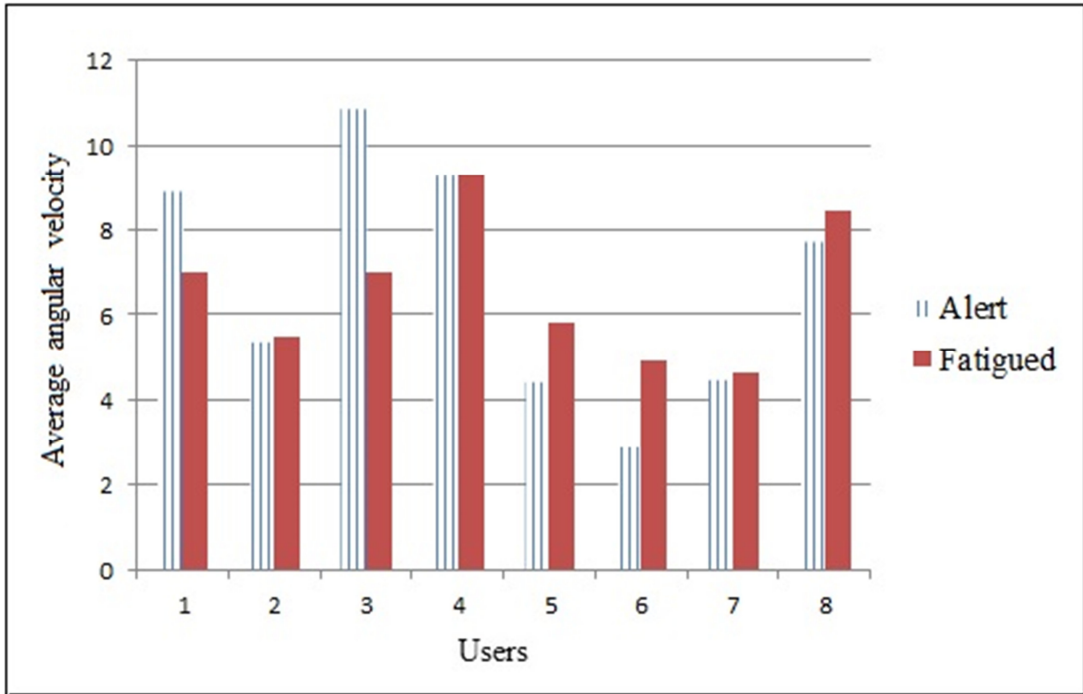


Figure 6-3: Average angular velocity

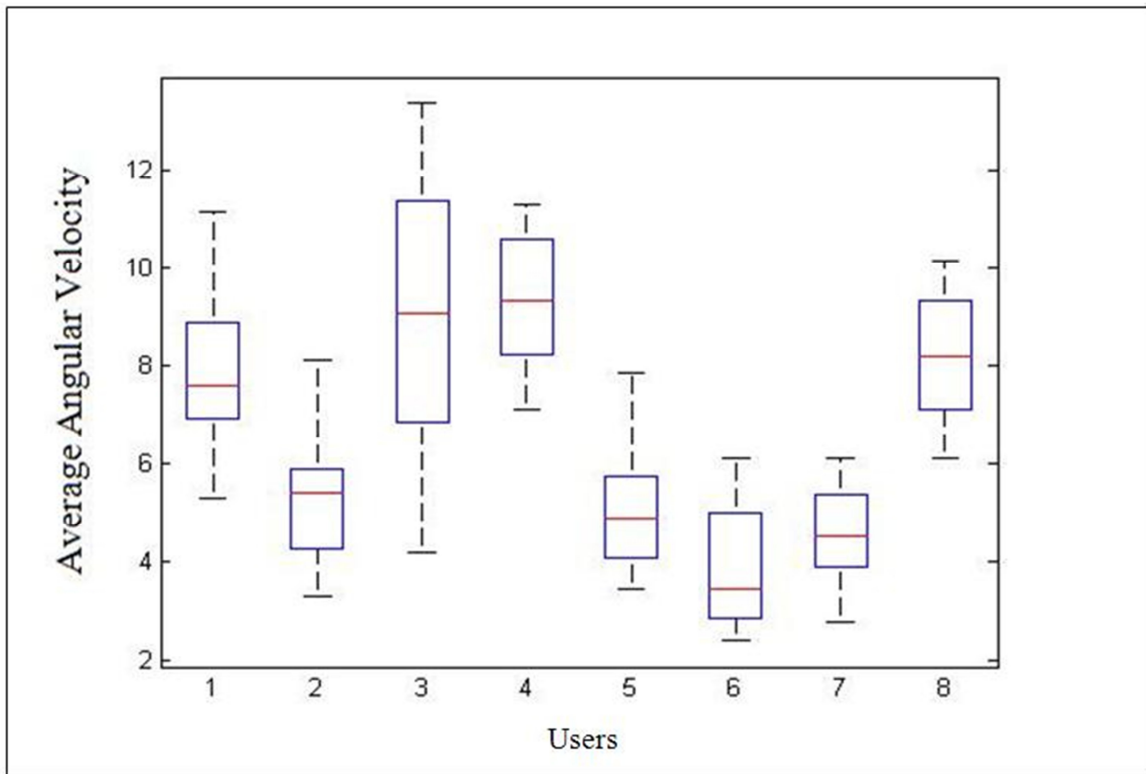


Figure 6-4: Average angular velocity (degree/second).

In conclusion, in a survey of Ontario police officers conducted by TRIF, 92.4% of the officers reported that they had stopped a driver suspecting that the driver had been under the influence of alcohol or drugs only to discover that they were fatigued instead (Traffic Injury Research Foundation, n.d.). This might support the hypothesis that fatigue can be reflected on the data from the steering wheel since impaired drivers also tend to have difficulty driving straight and steering normally.

6.1.2 Gas Pedal

An excess of speed is considered to be one of the characteristics of sleep related accidents (Pack et al., 1995). Also, 84.3% of Ontario police officers associate inconsistent speed with fatigued driving (Traffic Injury Research Foundation, n.d.).

It is widely known that fatigue causes muscles to relax. As result, a driver might unintentionally apply more pressure to the gas pedal, causing the speed to increase. Fatigue also decreases the level of attention of the driver. As a result, the driver might not be aware of his/her current speed.

In our experiment, the data acquired data from the gas pedal shows differences depending on the driver's state as shown in Table 6-3. In general, the average pressure applied to the gas pedal while driving fatigued is less than the average when driving fully alert, which indicates a lower speed. This finding might not contradict other findings in different studies that associate an excess of speed with fatigue, if we take into consideration the size and the resistance of the pedal used in the experiment, how users place their foot on the pedal, and their seating is different than in a real car. Yet, some drivers in the experiment recorded a higher average of pressure applied to the gas pedal while they were fatigued. This may shed some light on the differences in the driving styles between drivers, which shown in Figure 6-5 and Figure 6-6.

Table 6-3: Average pressure applied to the gas pedal.

User	Alert	Fatigued
1	28.92	26.30
2	28.48	29.93
3	33.68	25.12
4	27.86	26.03
5	23.77	27.40
6	26.33	23.30
7	27.67	26.30
8	26.72	34.05
Total	223.43	218.42
Total Average	27.93	27.30

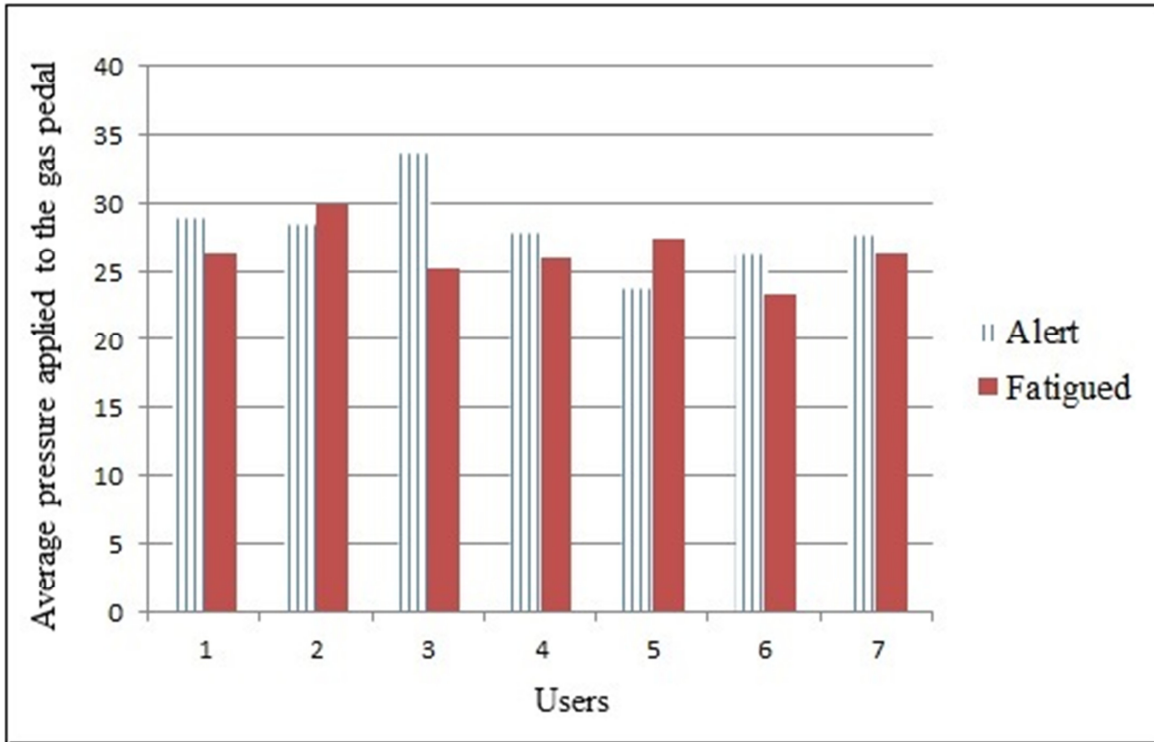


Figure 6-5: Average pressure applied to the gas pedal.

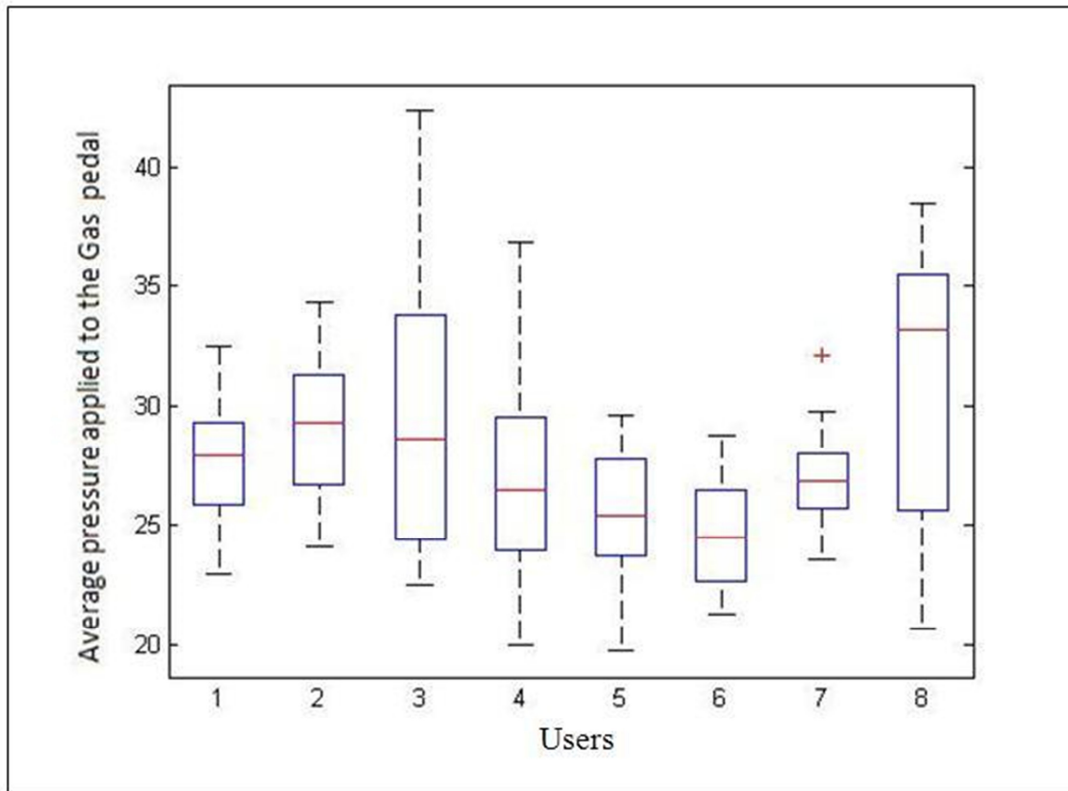


Figure 6-6: Average pressure applied to the gas pedal.

6.1.3 Brake Pedal

The deterioration of a driver's performance as result of fatigue (Brown, 1994) might be reflected on the usage of the brake pedal. Drivers used the brake less when they were fatigued. Furthermore, some of them missed the traffic light as a result of being inattentive. The data indicates that drivers used the brake more often when they were alert, in order to correct their speed, slowdown in a curve when needed, or stop when there was traffic as shown in Table 6-4. Also, Figure 6-7 shows some differences among users.

Table 6-4: Average pressure applied to the brake pedal.

Users	Alert	Fatigued
1	2.22	0.96
2	1.42	1.09
3	1.53	0.41
4	1.32	1.11
5	1.17	0.64
6	1.21	0.71
7	1.47	0.58
8	3.00	4.17
Total	13.34	9.66
Total Average	1.67	1.21

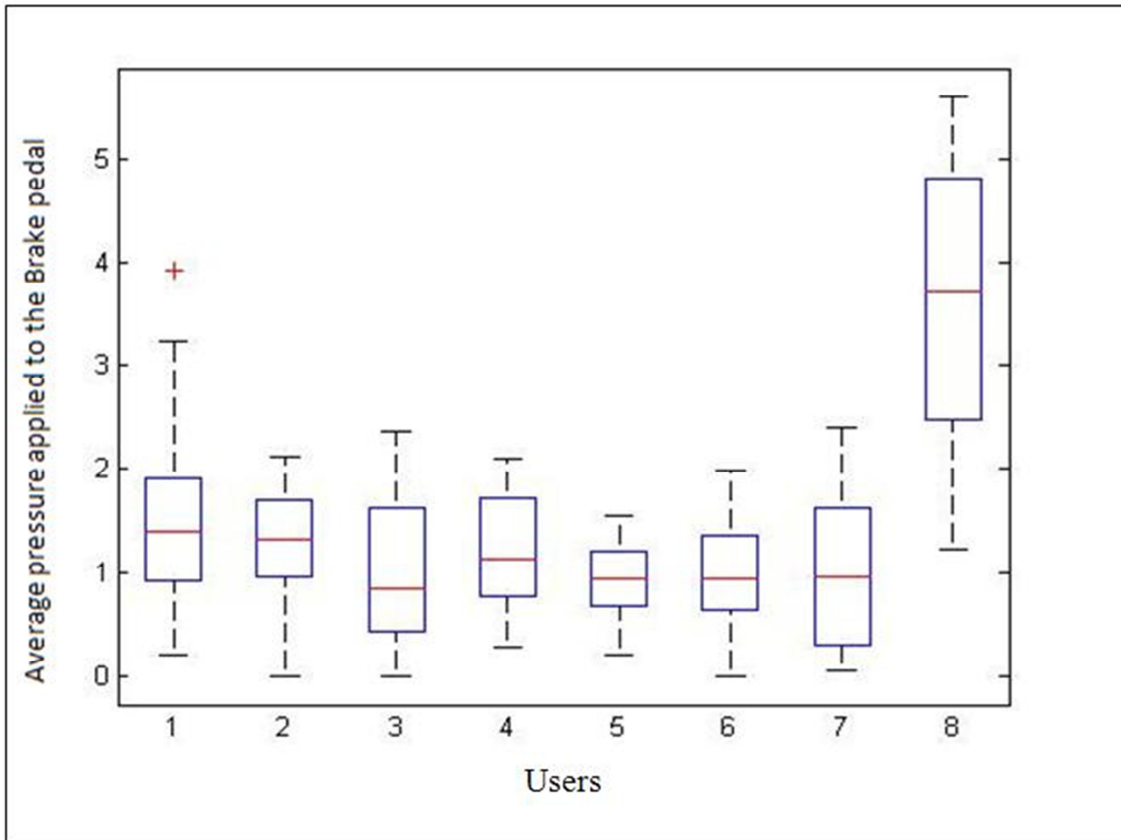


Figure 6-7: Average pressure applied to the brake pedal.

6.1.4 Grip Force

Fatigue can also be detected through grip force, as in (Chieh et al., 2003). As mentioned previously, fatigue causes muscles to relax, and the collected data shows that the average grip force for most users is less when they are fatigued as shown in Table 6-5. Yet, for other users it is higher, and that could be result of the way they grip the steering wheel. Some users would grip the steering wheel with a few fingers while their palms relax on the front of it;

when these drivers are fatigued, they sometimes place their palms on the pressure sensor. This shows us that driving behaviour differs from one driver to another as illustrated in Figure 6-8 and Figure 6-9.

Table 6-5: Average grip force.

Users	Alert	Fatigued
1	348	431
2	371	294
3	291	237
4	375	307
5	428	347
6	433	396
7	352	324
8	393	290
Total	2991	2626
Total Average	374	328

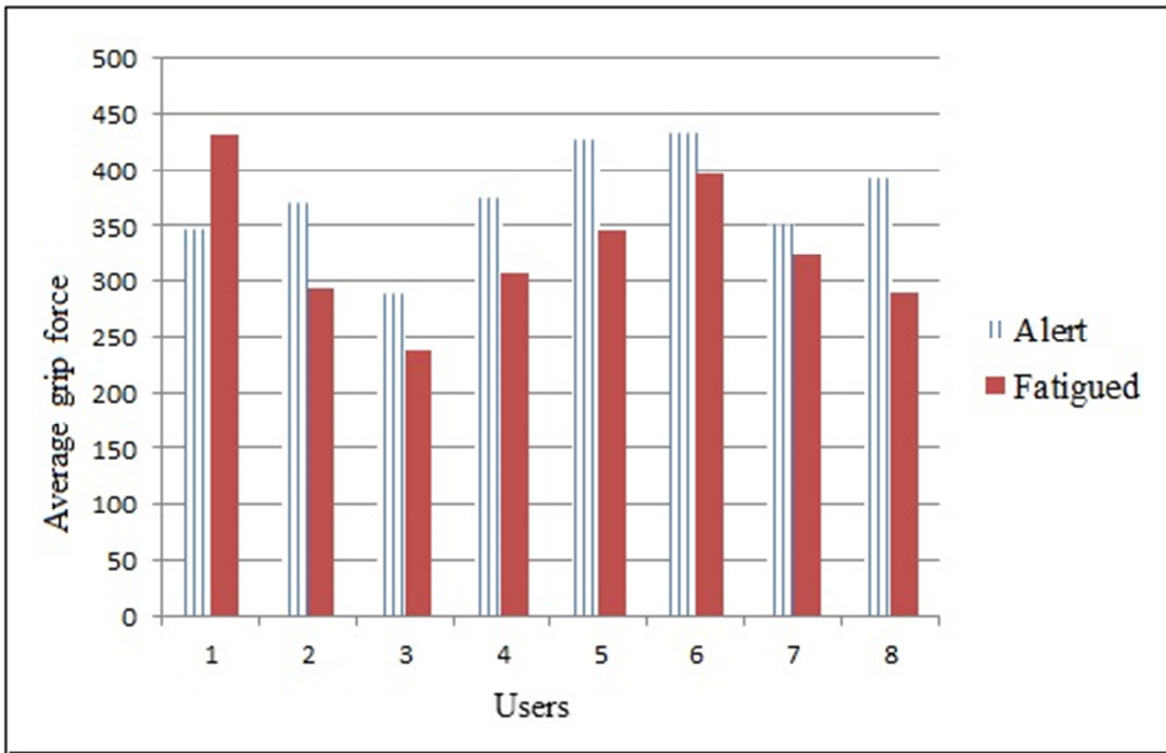


Figure 6-8: Average grip force.

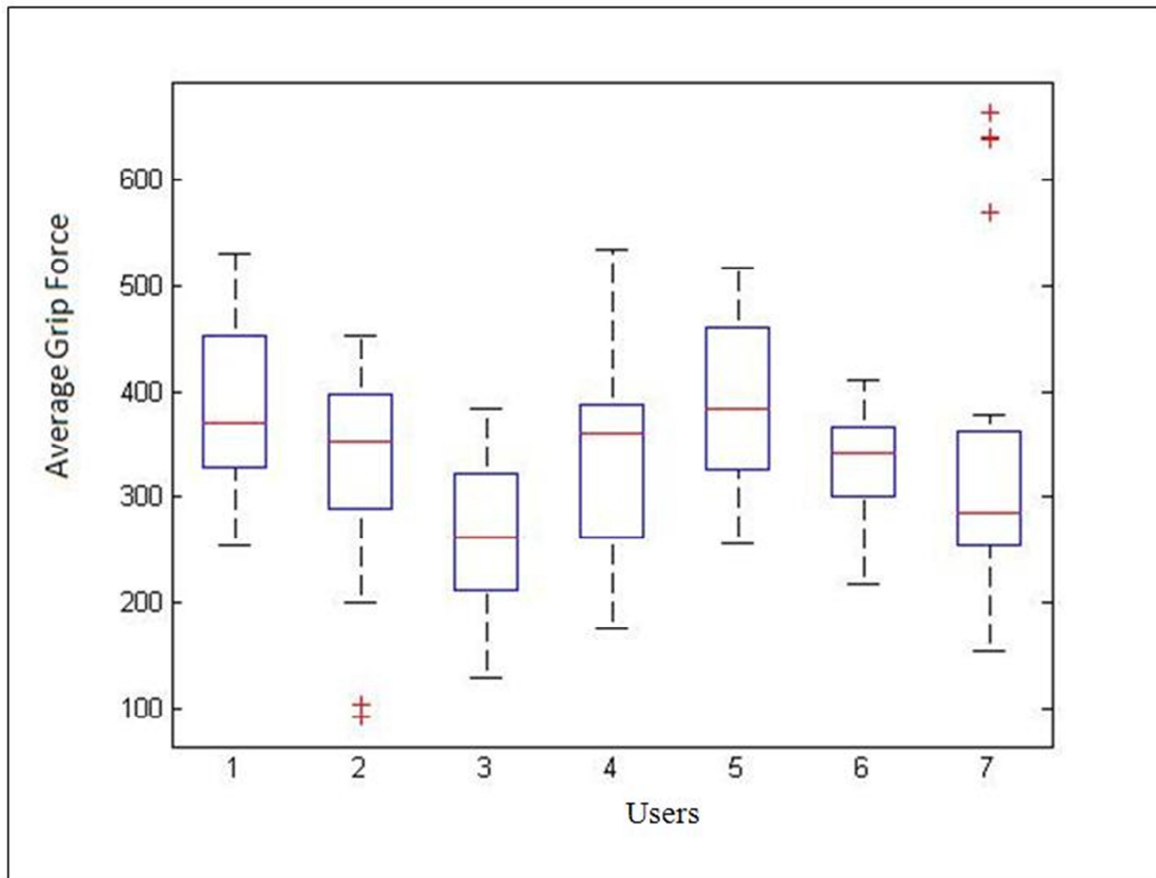


Figure 6-9: Average grip force.

6.2 Testing the System

A Bayesian Network was created by using *Netica* 4.16 (*Netica* is a registered trademark of Norsys Software Corporation). *Netica* has a graphical user interface, allowing us to take screen shots and present them here.

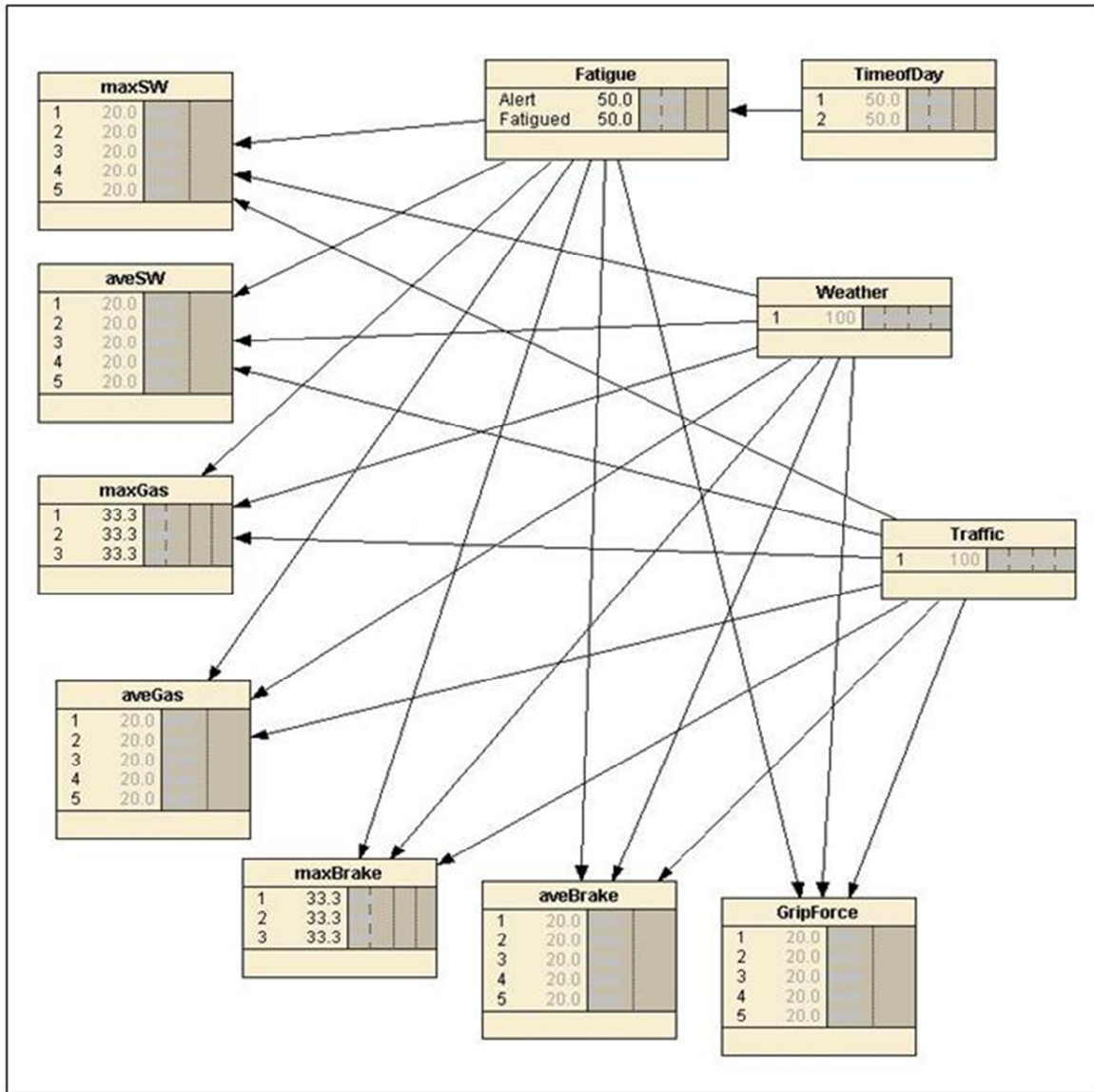


Figure 6-10: A screenshot of the system.

In order to test the system's accuracy, we followed several steps. First, since the system is personalized, we created a BN with the same structure as shown in Figure 6-10, for each user. Then, we fed the system with the users' driving data, excluding the cases that would be tested. Conditional probability tables in BN can be entered manually, based on human

expertise in the domain, or they can be learned from the data. In our experiment, the CPTs were learned from the data, and they are different from one user to another. Each user has a personalized CPT, since driving styles differ from one user to another. As a result, the inferred CPTs from the data of each user had different values. For example, Figure 6-11 shows the CPTs of the average angular velocity of the steering wheel for three users, and we can see the differences between them.

Fatigue	Weather	Traffic	1	2	3	4	5
1	1	1	6.25	43.75	6.25	25	18.75
2	1	1	21.429	14.286	21.429	7.143	35.714
Fatigue	Weather	Traffic	1	2	3	4	5
1	1	1	53.333	20	26.667	6.67e-05	6.67e-05
2	1	1	6.667	33.333	26.667	13.333	20
Fatigue	Weather	Traffic	1	2	3	4	5
1	1	1	8.33e-05	16.667	58.333	25	8.33e-05
2	1	1	13.333	26.667	13.333	26.667	20

Figure 6-11: Conditional probability tables of different users.

After the learning process, the parameters of the BN would be as shown in Figure 6-12.

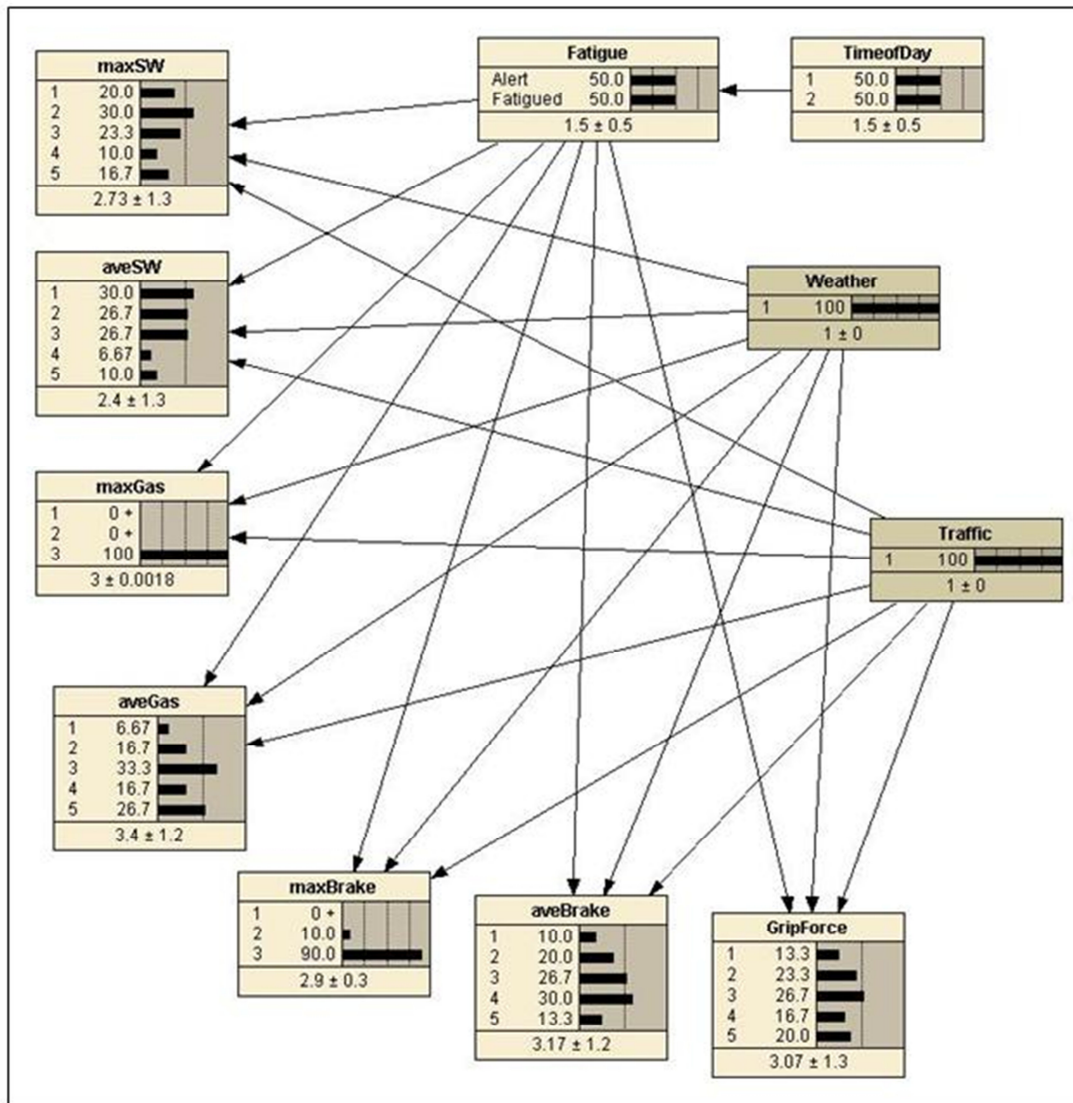


Figure 6-12: A screenshot of the system after updating the parameters.

To test the system, we then entered the parameters of the excluded cases from the training data set. The parameters entered in BN are called evidence, and by using a junction tree algorithm that BN provided, we inferred the unobserved state, which was Fatigue as shown in Figure 6-13. These steps were repeated for each user.

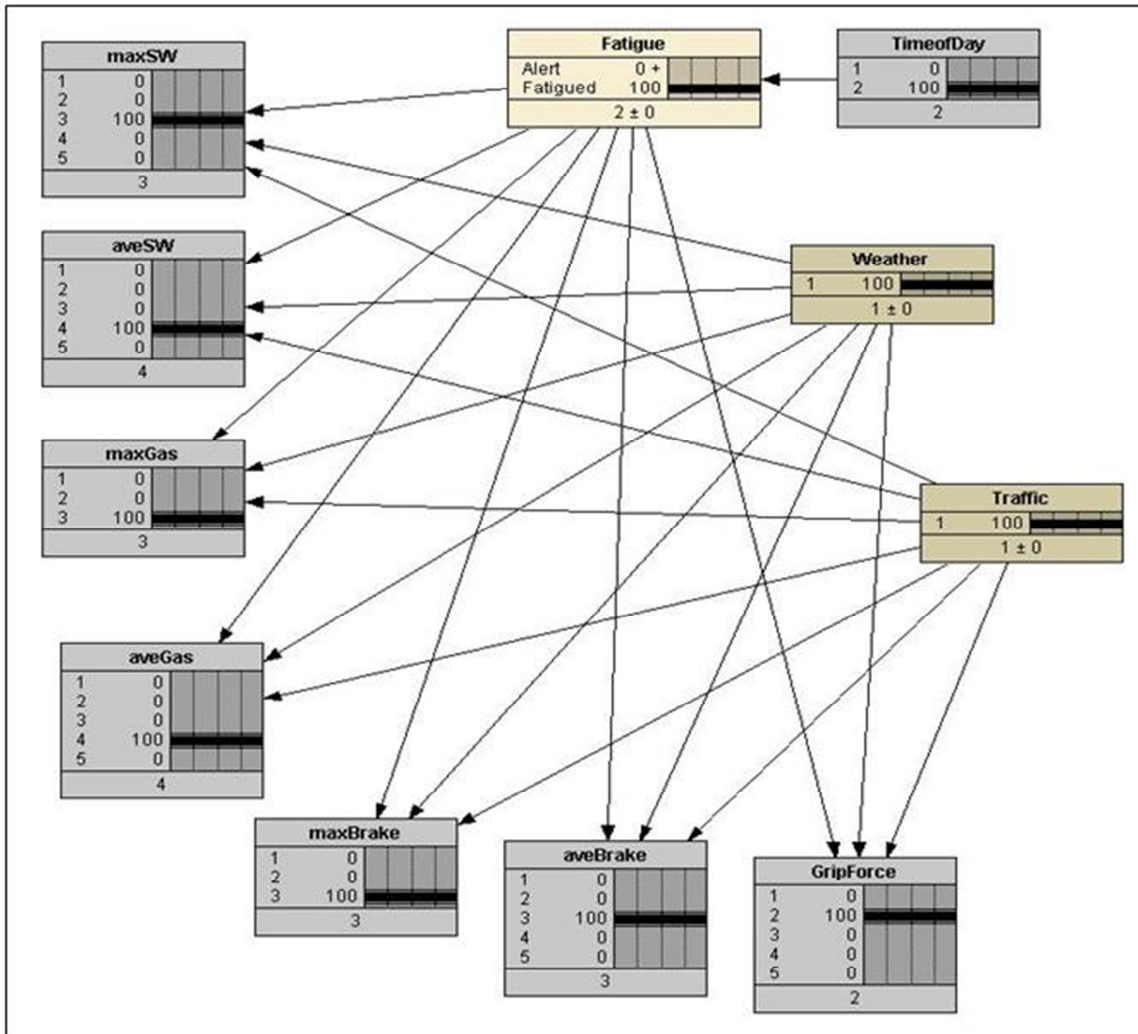


Figure 6-13: A screenshot of the inferring (entering of evidence).

6.3 System Accuracy

The result of the system was compared to the Karolinska Sleepiness Scale (KSS). Several studies have validated the KSS accuracy as mention in Section 5.3. Indeed, KSS is commonly used to validate the result of fatigue detection techniques as in (Gillberg et al.,

1994; HORNE & REYNER, 1996; Ingre, ÅKerstedt, Peters, Anund, & Kecklund, 2006; Kaida et al., 2006).

Moreover, there are two things that should be taken into consideration when it comes to the system's accuracy. First, the training data used in the learning process was considerably small. Users were asked to drive for a total of one hour, and the system was designed to make a decision every two minutes. We therefore had approximately 30 cases per user. Indeed, the more training data we have, the more accurate the system will be. Second, although all users had a valid driver's license, driving in a simulator is different than in real life. We noticed that users who had experience with video games were more comfortable driving in the experiment. Most of the users did have experience with video games, but the users who did not were not as comfortable with the simulator, which resulted in lower detection accuracy for them, since their driving was not as smooth as the rest of the users.

Finally, in order to have the users drive while fatigued, they were asked to drive at times when they were most likely to be fatigued. These times were chosen based on studies that determined peak sleep times. As a result, the probability of being fatigued at those specific times of the day is very high. However, even if we exclude the Time of the Day node from BN, the system is still accurate

6.3.1 Personalized BN

The BN for fatigue detection is personalized since the driving style differs from one driver to another, as has been shown in the previous sections of this thesis. We designed a BN with the same structure for each user, and it was trained only by the data acquired from this user. Table 6-6 shows the average fatigue detection for each user including the “Time of Day” node as well as the average excluding the “Time of Day”. The reason for including and excluding this particular node is explained in the previous section.

Table 6-6: Average accuracy for the users.

	User 1	User 2	User 3	User 4	User 5	User 6	User 7	User 8	average
Including "Time of Day"	100	100	100	100	100	100	100	100	100
excluding "Time of Day"	97.36	97.98	95.11	97.17	99.05	89.78	91.5	98.57	95.81

6.3.2 Generalized BN

In contrast to our proposed personalized BN, a general BN was tested. This generalized BN has the same structure as shown in Figure 6-14; the only difference is that it is trained on the

data from all the users. The learning process was not separated for each user. Due to the differences in driving styles, the generalized BN was not as accurate as the personalized BN.

In order to test the generalized BN, we had to re-do the discretization process since the maximum value of each node is the highest value obtained among all the users, as is the case with the lowest value. After subtracting the highest and lowest values of the following nodes: “Maximum angular velocity of the steering wheel”, “Average angular velocity of the steering wheel”, “Maximum pressure applied to the gas pedal”, “Average pressure applied to the gas pedal”, “Maximum pressure applied to the brake pedal”, “Average pressure applied to the brake pedal”, and “Average pressure applied on the force sensing sensor” the result was divided by 5 as we did in the discretization process of the personalized BN. The average accuracy without including the “Time of Day” node was 65%.

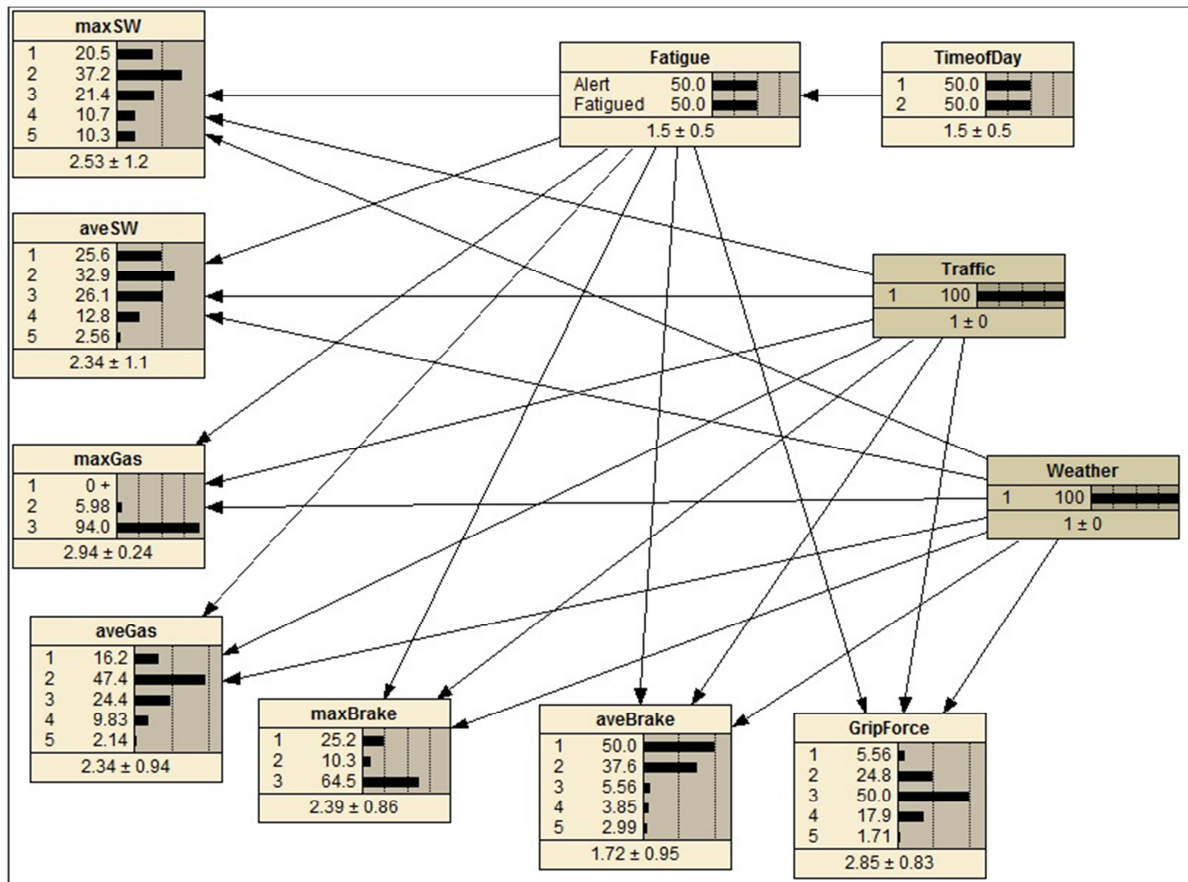


Figure 6-14: A screenshot of the system after updating the parameters of all the users.

In another attempt to increase the accuracy, we increased the number of states for the aforementioned nodes to 10 instead of five. The reason for increasing the number of states was that the range between the highest and the lowest value was considered to be wide, since the highest value could be reached by a user while the lowest could be reached by a different user. However, in this scenario, the average accuracy without including “Time of Day” was 68%. As we can see, the difference was not significant, even after increasing the number of

states. Moreover, increasing the states more than that would result in a significant amount of missing data that might jeopardize the reliability of the system.

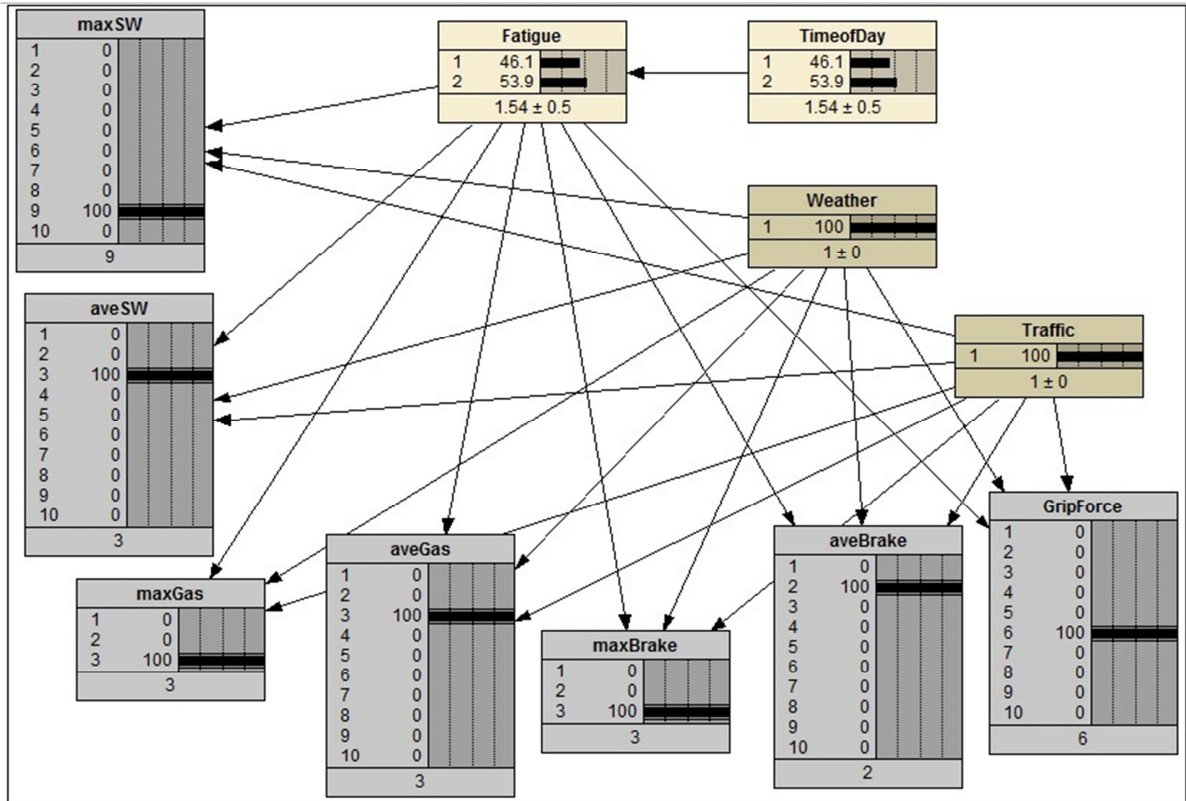


Figure 6-15: A screenshot of the system after increasing the nodes' states.

Chapter 7 Conclusion and Future Work

This chapter concludes the thesis findings, and provides suggestions for future work.

7.1 Conclusion

Fatigue is a hazardous issue in transportation, causing a significant loss of lives and money, every year. In order to save lives and money, this issue has to be addressed from different perspectives and angles. For example, the media can educate people regarding the possible consequences of driving while fatigued. Indeed, the need for an accurate system of fatigue detection is rising since the number of fatigue related accidents is considered to be high.

Therefore, we propose a personalized BN with parameters that can be acquired in modern cars, as they are equipped with computing facilities. Personalizing the BN overcomes the issue of individual differences that form an obstacle in detecting fatigue accurately. Furthermore, the conducted study yielded results showing a significant difference in accuracy if the BN was not personalized. Finally, the proposed system does not use any intrusive or wearable sensors, which makes it more comfortable for drivers. Also, the system has the ability to detect fatigue under various conditions, since it has the ability to learn.

7.2 Limitations

There were several limitations that accompanied this study. For instance, the size of the training data set was small since users drove for only one hour. Also, the system was tested on 8 users, which is considered to be a small number of users. Furthermore, the experiment was conducted in a lab, using a driving simulator.

7.3 Future Work

The system has achieved satisfactory accuracy, yet can still be improved. For instance, adding more parameters to the system may increase its accuracy and reliability. An example of these parameters could be the duration of driving, the age, and other parameters that could cause or reflect fatigue.

This study was conducted on a driving simulator, which may be different than real life. Also, the system was tested in one driving condition, and used a small training data set. Therefore, it may be necessary to test the system in real life, on more users, and in different conditions.

Moreover, the system could be improved by implementing a suitable countermeasure. The countermeasure can vary from playing a warning sound or using a haptic feedback as in (Rahman et al.) to sending warning messages to a specialized authority center or to nearby cars.

Furthermore, the BN can be dynamic, which gives it the ability to update its parameters. As a result, this ability may increase both the accuracy and the reliability of the system. A further study to compare the results might be needed.

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