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# Real-time drowsiness detection using wearable, lightweight EEG sensors

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# Real-time drowsiness detection using wearable, lightweight EEG sensors

Rohit

Thesis submitted to the  
Benjamin M. Statler College of Engineering and Mineral Resources  
at West Virginia University

in partial fulfillment of the requirements  
for the degree of

Master of Science  
in  
Computer Science

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Keywords: EEG, Drowsiness Detection, Fatigue, EEG Spectral Analysis, Alpha, Delta,  
Theta, Beta, Gamma

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# ABSTRACT

Real-time drowsiness detection  
using wearable, lightweight EEG sensors

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Driver drowsiness has always been a major concern for researchers and road use administrators. It has led to countless deaths accounting to significant percentile of deaths world over. Researchers have attempted to determine driver drowsiness using the following measures: (1) subjective measures (2) vehicle-based measures; (3) behavioral measures and (4) physiological measures.

Studies carried out to assess the efficacy of all the four measures, have brought out significant weaknesses in each of these measures. However detailed and comprehensive review has indicated that Physiological Measure namely EEG signal analysis provides most reliable and accurate information on driver drowsiness. In this paper a brief review of systems, and issues associated with them has been discussed with a view to evolve a novel system based on EEG signals especially for use in mine vehicles .

The feasibility of real-time drowsiness detection using commercially available, off-the-shelf, lightweight, wearable EEG sensors is explored. While EEG signals are known to be reliable indicators of fatigue and drowsiness, they have not been used widely due to their size and form factor. But the use of light-weight wearable EEGs alleviates this concern. Spectral analysis of EEG signals from these sensors using support vector machines is shown to classify drowsy states with high accuracy.

The system is validated using data collected on 23 subjects in fresh and drowsy states. The EEG signals are also used to characterize the blink duration and frequency of subjects. However, classification of drowsy states using blink analysis is shown to have lower accuracy than that using spectral analysis.

# Acknowledgements

First, I want to thank my committee chair and advisor, Dr. Vinod K. Kulathumani, for guiding me in the my research and providing me the opportunity to work with him and his other graduate students. This thesis work has been made possible with his constant support and guidance.

I also want to thank Dr. Yanfang Ye, Dr Yaser Fallah and Dr Vladislav Kecojevic for being a part of the my committee. I have had discussions with them which were important in my understanding of identifying and solving certain research oriented problems in my Thesis.

I would like to thank my current co-workers for helping me out in collecting the data-set for this work. I want to thank my co-workers Mr Rahul Kavi and Mr Venkata Raghava Siva Naga Shashank Sabniveesu with whom I've had the pleasure of working with. They have been extremely helpful, supportive in building my understanding of the subject. I've learned loads from them in discussions with them and also the valuable code debugging sessions we've had together. I would remain glad for having Mr Masahiro Nakagawa, Mr Ajay Krishna Teja and Mr Priyashraba Misra as my lab-mates for the informative discussions I had with them that helped me appreciate different concepts from various fields adjoining Computer Science.

Last but not the least, I want to express my gratitude to my family. My parents and my wife have been very encouraging on my decision to go to grad school. Their support has been relentless and a constant motivation to my desire of pursuing Computer Science in school.

# Contents

<b>Acknowledgements</b>	<b>iii</b>
<b>List of Figures</b>	<b>vi</b>
<b>List of Tables</b>	<b>viii</b>
<b>1 Introduction</b>	<b>1</b>
1.1 Background and objective . . . . .	1
1.2 Related work . . . . .	5
1.3 Summary of findings . . . . .	12
1.4 Impact beyond surface mining . . . . .	13
<b>2 System Description</b>	<b>15</b>
2.1 Data collection . . . . .	15
2.2 Feature selection . . . . .	17
2.3 Classification approaches . . . . .	18
2.3.1 Linear Discriminant Analysis . . . . .	18
2.3.2 Support Vector Machines . . . . .	19
2.4 Experiment description . . . . .	21
2.4.1 Per-subject training . . . . .	21
2.4.2 Cross-subject training . . . . .	22
2.4.3 Metrics . . . . .	22
2.5 Blink characteristics . . . . .	23
<b>3 Performance Analysis</b>	<b>25</b>
3.1 Parameter and Kernel Decision . . . . .	25
3.2 Blink Detection . . . . .	26
3.2.1 Subject Based Analysis . . . . .	26
3.2.2 Cross Subject Validation . . . . .	27
3.3 Spectral Based Drowsiness Detection . . . . .	27
3.3.1 Subject based analysis . . . . .	28
3.3.2 Cross Subject Validation . . . . .	29
3.3.3 Temporal aggregation . . . . .	30

<b>4</b>	<b>Conclusion and Future work</b>	<b>34</b>
4.1	Conclusions . . . . .	34
4.2	Future work . . . . .	35
	<b>References</b>	<b>36</b>

# List of Figures

1.1	MUSE brain sensing headband [1]. The system is battery operated and equipped with Bluetooth radio for data collection. EEG signals were recorded from one of the forehead sensors. . . . .	7
2.1	Subject wearing a MUSE headband during data collection. The subject is shown operating a driving simulator. . . . .	16
2.2	(a) Example signal patterns corresponding to a blink and (b) Example signal patterns that do not correspond to a blink . . . . .	21
3.1	(a) Bar graph of classification accuracy per subject with LDA classifier using Blink data and (b) Bar graph of classification accuracy across subject with LDA classifier. The classifiers are tested using an 10-fold cross validation for per subject and 22-fold cross validation for across subject, i.e., 10 different set of training and test data are randomly picked for each subject in a 4 : 1 train:test ratio for the per subject and 22 subjects for training and the remaining one subject for testing. The average results per subject are reported.	27
3.2	(a) Bar graph of classification accuracy per subject with LDA classifier and (b) Bar graph of classification accuracy per subject with SVM classifier. The classifiers are tested using an 10-fold cross validation, i.e., 10 different set of training and test data are randomly picked for each subject in a 4 : 1 train:test ratio. The average results per subject are reported. . . . .	28
3.3	Comparison of precision, recall and accuracy on a per-subject basis using SVM and LDA classifiers with spectral features of EEG signals. The classifiers are tested using an 10-fold cross validation, i.e., 10 different set of training and test data are randomly picked for each subject in a 4 : 1 train:test ratio. . . .	29
3.4	Comparison of precision, recall and accuracy in a cross subject validation using SVM and LDA classifiers with spectral features of EEG signals. We trained the classifier using data from 22 subjects and test on the remaining one subject. The box plot captures the variations in classification performance across the 23 subjects. . . . .	30
3.5	(a) Impact of temporal aggregation on accuracy with LDA classifier and (b) Impact of temporal aggregation on accuracy with SVM classifier . . . . .	31

3.6	(a) Impact of temporal aggregation on sensitivity (recall) of drowsiness detection with LDA classifier and (b) Impact of temporal aggregation on sensitivity (recall) of drowsiness detection with SVM classifier . . . . .	31
3.7	Comparison of precision, recall and accuracy on a per-subject basis with a blink based analysis and spectral analysis. An SVM classifier is used for both. The classifiers are tested using an 10-fold cross validation, i.e., 10 different set of training and test data are randomly picked for each subject in a 4 : 1 train:test ratio. . . . .	32
3.8	Comparison of precision, recall and accuracy in cross-subject validation with a blink based analysis and spectral analysis. An SVM classifier is used for both. We trained the classifiers using data from 22 subjects and test on the remaining one subject. The box plot captures the variations in classification performance across the 23 subjects. . . . .	33

# List of Tables

2.1	List of features . . . . .	18
2.2	Parameters for Blink Detection Algorithm . . . . .	24
3.1	Accuracy of Kernels of SVM . . . . .	25
3.2	Accuracy of Parameter of RBF SVM Kernel . . . . .	26

# Chapter 1

## Introduction

This chapter introduces the topic of driver drowsiness and how it is becoming a growing concern in the mining industry. In this chapter, we also look at the related work which has been used previously for drowsiness detection and why these methods have either not been effective or were practically impossible to implement in everyday scenario. The effects of Drowsiness on other areas apart from mining industry is examined to assess as to how much it is effecting the other areas.

### 1.1 Background and objective

Vehicle Accident data in early 2015 indicated that approximately 6,000 lives are lost each year due to drowsy driving. Details available show that alcohol and poor sleep affect the drivers almost similarly, inducing inattentiveness and sluggishness to react.

In 2014 there were 846 fatalities (2.6% of all fatalities) recorded in National Highway Traffic Safety Administration's (NHTSAs) Fatality Analysis Reporting System(FARS) database that were drowsy-driving-related. These reported fatalities (and drowsy-driving crashes overall) have remained largely consistent across the past decade. Between 2005 and 2009 there was an estimated average of 83,000 crashes each year related to drowsy driving. This annual average includes almost 886 fatal crashes (2.5% of all fatal crashes), an estimated 37,000

injury crashes, and an estimated 45,000 property damage only crashes.

Fatigue and drowsy driving across the nation has resulted in thousands of crashes annually and is a substantial threat to public safety. One research indicates that almost 20 percent of all serious car crash injuries are associated with driver sleepiness, independent of alcohol effects (Connor et al. 2002).

Laws against drunk driving have been successful but may not work to reduce drowsy driving. The state of New Jersey considers a driver who has been awake for 24 hours to be a reckless driver and falls in the same class as an intoxicated driver. Its usually impossible to determine the cause of a fatal crash caused due to drowsy driving. However, drowsy driving accidents usually involve only one vehicle for a single driver and the injuries may be serious or fatal. Also, skid marks or evidence of other maneuvers are not found at crash scene.

Besides this, no blood, breathalyzer, or other objective test can determine if the cause of a crash was fatigue or drowsy driving. With no such specific test of level of drowsiness, police officers have difficulty identifying driver fatigue as cause to a crash; hence fatigue-related crashes are mostly under-reported and maybe there are significantly more crashes than statistics indicate.

Usually everyone is aware of the dangers of drinking and driving, many fail to understand the extent of dangers and fatalities that may occur due to driving while extremely fatigued. Research indicates that fatigue appears to be second only to alcohol as the most common cause of serious injury in vehicle crashes (Mitler 1989). Drowsy drivers have a slower reaction time, decreased awareness of their environment, and lack of judgment in their actions similar to drunken drivers.

Falling asleep at the wheel is dangerous, but being sleepy affects ability to drive safely even if drivers don't fall asleep. Research has proven that drowsiness

- Makes drivers less able to pay attention to the road.
- Affects information processing, short-term memory to slow reflexes for braking /steering.
- Affects a driver's ability to make good decisions and use unobliterated vision capacities.
- Decreases performance, vigilance and motivation
- Increases moodiness and aggressive behaviors

Researchers estimate that more than 70 million Americans suffered from a sleep disorder in 2005. (Institute of Medicine, 2005). Studies discussed at National Transportation Safety Board(NTSB) forum during October 2014 brought out that the drivers susceptible to drowsiness could be the following:

1. Drivers who do not get enough sleep.
2. Commercial drivers who operate vehicles such as tow trucks, tractor trailers, and buses.
3. Shift workers (work the night shift or long shifts).
4. Drivers with untreated sleep disorders such sleep apnea.
5. Drivers getting drowsy due to medications.

Discussing the stats made available to the Forum, they found that

1. An estimated 1 in 25 adult drivers (aged 18 years or older) report having fallen asleep while driving in the previous 30 days.
2. The National Highway Traffic Safety Administration estimated that drowsy driving was responsible for 72,000 crashes, 44,000 injuries, and 800 deaths in 2013. However, these numbers are underestimated and up to 6,000 fatal crashes each year may be caused by drowsy drivers.
3. Among nearly 150,000 adults aged at least 18 years or older in 19 states and the District of Columbia, 4%reported that they had fallen asleep while driving at least once in the previous 30 days.

4. Individuals who snored or usually slept 6 or fewer hours per day were more likely to report falling asleep while driving.

The NTSB forum during October 2014 discussed, in-vehicle technologies to mitigate drowsy driving by either detecting drowsiness or by alerting drowsy drivers avoid crashes. When the system detects a driver who is at risk of falling asleep, it sends a warning. These technologies currently available or still under development have undergone testing to determine user acceptance and effectiveness. However most have not proven to be acceptable so far.

Definitions of drowsy driving or driver fatigue rely on how the concept of fatigue is defined. Fatigue is a general term commonly used to describe the experience of being sleepy, tired, drowsy, or exhausted. While all of these terms have different meanings in research and clinical settings, they tend to be used interchangeably in the traffic safety and transportation fields.

My thesis is specifically motivated by the need for avoiding injuries and fatalities in surface mining operations. Despite the record of progress achieved in reducing fatal and non-fatal mining injuries in the United States (US), both the number and severity of the mining injuries remain unacceptable. A persistent area of concern in mine safety continues to be related to mining equipment (powered haulage, machinery and hoisting).

According to Mine Safety and Health Administration (MSHA) records [2, 3, 4], there were a total of 643 fatal injuries between 1995 and 2011 in US coal, metal, and non-metal mining attributed to mining equipment. This represents 68.8% of all mining fatalities in the US. The greatest proportion of fatalities is related to haul trucks (21.9%), front-end loaders (8.1%), dozers (6%) and miscellaneous equipment (36.5%).

Furthermore, a significant portion of these injuries have been linked to operator fatigue and drowsiness [5, 6]. As per a recent report [7], fatigue is implicated in approximately

69% of mining accidents involving haul trucks. Workers who sleep less than 7 – 9 hours in a 24-hour period are at high risk of fatigue related accidents. Monotonous and repetitive activities that provide little or no variance in mental stimulation will leave workers highly susceptible to fatigue.

Work using haulage equipment and pick-up trucks is typically done in two shifts, one day-time and one overnight. These shifts are long and strenuous. Moreover, the margin of error is often quite small and often a momentary lapse of attention with large trucks on dangerous terrain can lead to severe consequences.

Following countermeasures have been researched extensively: (1) subjective measures (2) vehicle-based measures; (3) behavioral measures and (4) physiological measures. Studies assessing the efficacy of all the four groups of measures, have found weaknesses in each of these measures. However is verified through tests that Physiological Measure namely electroencephalogram(EEG) signal analysis provides most reliable and accurate information on driver drowsiness.

The *objective* of this thesis work is to explore the feasibility of wearable, lightweight EEG sensors for detecting drowsiness in drivers in real-time so that precautionary measures can be taken to avoid an accident.

## 1.2 Related work

Given the importance of fatigue monitoring and drowsiness detection, there have been numerous technologies developed in the industry and academia to address these concerns. A detailed survey is presented in [8] and [9]. Fatigue monitoring solutions use a range of technologies such as monitoring blink patterns [10, 11, 12, 13, 14], monitoring eyelid closure [15], monitoring facial movements [16], monitoring heart rate variations [17, 18, 19], monitoring yawns [20], and monitoring head movements using accelerometers [21]. The use of Electro-Oculogram (EoG) to identify driver drowsiness through eye movements and orientation has

been explored in [22, 23].

Some researchers have used a combination of physiological signals such as heart rate, respiration rate, eye blinking and skin conditions for predicting fatigue [24, 25]. Drivers lane keeping indicators viz Standard Deviation of Lane Position (SDLP) and steering wheel movement (SWM) patterns have also been used for predicting fatigue [26, 27]. Wearable wrist bands that monitor sleep patterns of a subject over several days and use that to predict likelihood of fatigue, have been recently introduced. However, this is not a tool for real-time assessment of fatigue [28].

Vehicular-based metrics however are not completely related to drowsiness. SDLP can also be caused by poor attentiveness in driving, including driving under the influence of alcohol / drugs /depressants etc [29, 30, 31]. Also the concept of lane maintenance is not particularly relevant in a surface mine terrains. SWMs work in very limited situations because they are too dependent on the geometric characteristics of the road, also on adopted environment as well as on the kinetic characteristics of the vehicle[32].

Steering wheel patterns are hard to monitor for huge trucks as well. Reliably measuring physiological signals such as heart rate, respiration rate, skin conditions and Electro-Oculograms require electrodes and probes to be attached, which is intrusive and bothersome. To address this, there has been some research on measuring physiological signals in a non-intrusive way by placing electrodes on the steering wheel or on the drivers seat [33, 34]. However, the accuracy of such a nonintrusive physiological system is relatively less due to movement artifacts and errors that occur due to improper electrode contact.

There have been other efforts using unorthodox and discretely differing approaches. Development of drowsiness scale namely Karolinska Sleepiness Scale (KSS), a nine-point scale that has verbal anchors for each step led to several researches by Hu et al [35], Portouli et al [36], and Ingre et al [37]. However, difficulty in obtaining drowsiness feedback from a driver in a real driving situation, and subjective ratings, despite being useful in determining

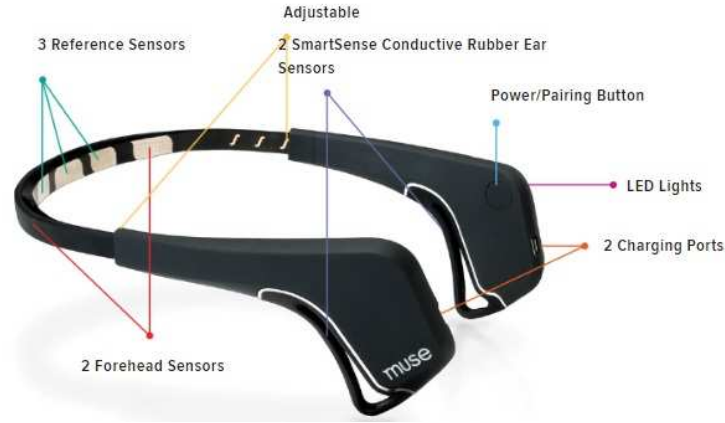


Figure 1.1: MUSE brain sensing headband [1]. The system is battery operated and equipped with Bluetooth radio for data collection. EEG signals were recorded from one of the forehead sensors.

drowsiness in a simulated environment, cannot be suitable for the detection of drowsiness in a real environment.

To address this, there has been some research on measuring physiological signals in a non intrusive way by placing electrodes on the steering wheel or on the drivers seat [38, 39]. However, the accuracy of such a non-intrusive physiological system is relatively less due to movement artifacts and errors that occur due to improper electrode contact. In comparison to all the above technologies, camera based monitoring is relatively non intrusive and easier to obtain.

Moreover, advances in portable cameras and Computer Vision techniques have made it feasible to perform real-time monitoring of a drivers face. Therefore, among all these technologies, monitoring blink patterns [10, 11, 12, 40, 41] and measuring percentage of eye closure [15] have been relatively more popular for fatigue monitoring in surface mining vehicles.

Fairly large research focus had also been on Behavioral Measures as displayed by drowsy person like irregular facial movements, including rapid and regular blinking, nodding of head, and yawning [40]. Most of studies focused on blinking [40, 42, 43]. PERCLOS (percentage of eyelid closure over the pupil over time, reflecting slow eyelid closures, or droops, rather

than blinks) [44, 45, 46, 15].

This measure is considered to predict drowsiness [45] and has been used in Seeing Machines [47] and Lexus [48]. Some researchers have also tried minor behavioral patterns also. Some research is still going on based on yawn, head movement and eyelid blink.

PERCLOS or percentage eye closure is a commonly used metric for detecting drowsiness. The basic idea here is to observe the blinking patterns of a subject and compute the percentage of time that the eyes are more than 80% closed[49]. Vision based systems are most commonly used for determining PERCLOS. A camera is focused on the subject's face and Computer Vision algorithms are used to extract the eye region and determine eye closure. Some such systems have recently been introduced in the market [47]. They are often supported with IR cameras so that the system can work in the dark.

In a recent report [50], I with my team have quantified the shortcoming of such a camera based approach for determining drowsiness, especially in harsh environments such as surface mines where there are tight space constraints for deploying such camera systems and the cameras are also subject to occlusions and vibrations. Camera based systems are hard to position inside a truck in such a way that it works for all drivers.

Occlusions such as a cap and the steering wheel often obstruct the view of the eyes. The system also fares poorly when there is a lot of glare in the subject's eyes either under too much sunlight or in the presence of bright road lights. When the driver wears glasses, the impact of glare is more pronounced [8].

The physiological signals (electrocardiogram (ECG), electromyogram (EMG), electrooculogram (EoG) and electroencephalogram (EEG)) have also been studied extensively in order to find their relationship with driver drowsiness [51, 52, 53, 54, 55]. The summary below describes previous works on driver drowsiness using different physiological signals

1. A combination of EEG, ECG, EoG sensors was used and data was classified using classifications LDA, LIBLINERA, KNN and SVM. 95-97% classification accuracy was achieved (31 drivers) [53]
2. ECG, sensors were used and data was classified using classifications Neural Network. 90% classification accuracy was achieved (12 drivers) [56]
3. EEG, sensors were used and data was classified using classifications Self-organizing Neural Fuzzy Inference Network. 96.7% classification accuracy was achieved (6 drivers) [57]
4. A combination of EEG, and EMG, sensors was used and data was classified using classifications Artificial Neural Network *ANN* Back Propagation Algorithm (Awake, Drowsy, Sleep). 98-99% classification accuracy was achieved (30 subjects) [58]
5. EEG sensors were used and data was classified using classification Mahalanobis distance. 80.7% classification accuracy was achieved (10 subjects)
6. A combination of EMG, and EoG sensors was used and data was classified using classifications SVM. 90% classification accuracy was achieved (37 subjects) [35]
7. A combination of EEG, EMG, EoG sensors was used and data was classified using classifications ANN. 97-98% classification accuracy was achieved (10 subjects) [58]
8. EEG sensors were used and data was classified using classification Hidden Markov Model. 84% classification accuracy was achieved (50 subjects)

The EoG signal were considered to identify driver drowsiness through eye movements [53, 35, 58]. Researchers have investigated horizontal eye movement by placing a disposable Ag-Cl electrode on the outer corner of each eye and a third electrode at the center of the forehead for reference [28].

The parameters - Rapid eye movements (REM) and Slow Eye Movements (SEM) which occur when a subject is awake and drowsy respectively, were detected[59]. The heart rate

(HR) also varies significantly between the different stages of drowsiness, such as alertness and fatigue[54, 60]. Therefore, heart rate determined by the ECG signal, Heart Rate Variability (HRV) a measure of the beat-to-beat (R-R Intervals) changes in the heart rate, [53, 56] was used to detect drowsiness. In HRV low (LF) and high (HF) frequencies fall in the range of 0.04 - 0.15 Hz and 0.14 - 0.4 Hz, respectively. HRV is a measure of the beat-to-beat (R-R Intervals) changes in the heart rate. The ratio of LF to HF in the ECG decreases progressively as the driver progresses from an awake to a drowsy state [55, 56].

The Electroencephalogram (EEG) is signal most commonly used to measure drowsiness. The EEG signal has various frequency bands, the delta band (0.5 - 4 Hz), FOR sleep activity, the theta band (4 - 8 Hz), related to drowsiness, the alpha band (8 - 13 Hz), for relaxation and creativity, and the beta band (13 - 25 Hz), identifying alertness [51, 57, 61, 62]. A decrease in the power changes in the alpha frequency band and an increase in the theta frequency band indicates drowsiness. Akin et al. observed that the success rate of using a combination of EEG and EMG signals to detect drowsiness is higher than using either signal alone [51].

A number of statistical features were extracted from the processed signal using Discrete Wavelet Transform (DWT) and Fast Fourier Transform (FFT) [51, 57, 61]. The extracted features were classified using Artificial Neural Networks (ANN), Support Vector Machines (SVM), Linear Discriminant Analysis (LDA), or other similar methods [53, 35, 58].

The driver drowsiness detection by using physiological signals was found to be highly reliable and accurate compared to other methods. The intrusive nature of sensors remained an issue to be addressed. To overcome this, researchers have used wireless devices to measure physiological signals in a less intrusive manner by placing the electrodes on the body and obtaining signals using wireless technologies like Zigbee [63], Bluetooth [64].

Measuring physiological signals in a non-intrusive way using the steering wheel [65, 38] or on the drivers seat [65, 39] as response tool helped in modernizing the setup and connecting it to androids based smartphones [66, 67]. The accuracy of non-intrusive stem is low

though these are used due to their user friendliness. The advantages and disadvantages of the different type of measures are researched as below

1. Subjective measures have advantage of being subjective but have a limitation of not being possible in real time. [37, 68]
2. Vehicle based measures have advantage of being non intrusive but are unreliable. [27, 69]
3. Behavioral Measures are non-intrusive and are easy to use but get affected by lighting conditions and background. [70, 71]
4. Physiological measures are reliable and accurate but have limitations of being intrusive. [65, 34]

Vehicle-based measures assess drowsiness when a lack of vigilance affects vehicle control or deviation. However, in some cases, vehicle-based parameters remained unaffected when the driver was drowsy [37]. Behavioral measures were evaluated as available real-time detection systems, by Lawrence et al.who observed that different illumination conditions affect the reliability and accuracy of the measurements [72].

Physiological measures bring out the true state of the driver at any point of monitoring time. They are usually intrusive in nature. Measurement of ECG however is less intrusive. The Electrodes used for measuring EoG signals can obstruct field of vision since they are close to eye. Non-obtrusive physiological sensors are futuristic in nature [66, 73].

Most of the EEG sensors have also been tested quite extensively in controlled clinical settings [8, 74]. However, these devices typically have many sensors and several dangling probes, and they have not been used widely in vehicular environments due to their size and form factor. Our experience with data collection in surface mines suggests that even helmets with embedded sensors are perceived as cumbersome for drivers of haul trucks.

Considering all above studies and conclusive evidence of the fact that EEG signals are known to be most reliable indicators of fatigue and drowsiness [75, 74], it is felt that use of some of the obtrusive sensors as pseudo non obtrusive sensors may be most optimum option.

Towards this approach, we have designed a novel system that uses lightweight brain sensing headbands, for drowsiness detection. The use of light-weight wearable EEGs alleviates this concern. Specifically, we used a device called MUSE manufactured by Interaxon Inc. [1](shown in Figure 1.1). MUSE is extremely lightweight, weighing just 61 grams. The system is battery operated and equipped with Bluetooth radio for data collection.

The EEG signal is recorded through forehead sensors and the device does not require use of gels for proper contact. These factors make MUSE convenient to use in the occupational settings. The original purpose of the device is to measure brain activity using EEG signals and aid in meditation. But we applied it for drowsiness detection and characterize its accuracy.

### 1.3 Summary of findings

We have used the MUSE wearable headband for collecting data from 23 subjects in fresh and drowsy states (experimental method is explained in Section 2.1). We carry out a spectral decomposition of the EEG data and train a support vector machine (SVM) classifier and a linear discriminant analysis (LDA) classifier on the data.

We first test the accuracy of the system on a per-subject basis. The classifiers are tested using an 10-fold cross validation, i.e. 10 different set of training and test data are randomly picked in a 4 : 1 train:test ratio. LDA yields 76% accuracy and SVM yields 81% accuracy on average in determining fresh and drowsy states. We then perform a cross-subject validation

with a one subject left out strategy.

In other words, we trained the classifier using data from 22 subjects and test on the remaining one subject. This yields 68% accuracy using LDA and 74% accuracy using SVM classifier. A further breakdown illustrates that the precision is higher than sensitivity and thus the system is less conducive to false positives in drowsiness detection. The fact that accuracy is high even in cross subject validation shows that the system can be used for real-time drowsiness detection using previously trained classifiers.

We then used the EEG signals to determine blink patterns of each subject. We computed the blink duration and the number of blinks per second for each subject in fresh and drowsy states. We used these two features to train an SVM classifier. However this system yields 72% accuracy on a per-subject basis and 60% accuracy under cross-subject validation and thus it significantly under performs when compared with spectral analysis using SVM. Moreover, the accuracy shows a larger range across different subjects and for some subjects the values are as low as 10%. Thus, our results show that spectral analysis of the EEG signal is a more reliable indicator of drowsiness, especially when inter-person variations are considered.

## 1.4 Impact beyond surface mining

Driver drowsiness and fatigue are concerns even outside the surface mining industry. Examples include drivers of passenger vehicles, truck fleets, air plane pilots and air traffic controllers. According to the National Sleep Foundation's 2005 Sleep in America poll, 60% of adult drivers about 168 million people say they have driven a vehicle while feeling drowsy, and more than one-third, (37% or 103 million people), have actually fallen asleep at the wheel [8].

In fact, of those who have nodded off, 13% say they have done so at least once a month. Four percent approximately eleven million drivers admit they have had an accident or near accident because they dozed off or were too tired to drive. The National Highway

Traffic Safety Administration conservatively estimates that 100,000 police-reported crashes are the direct result of driver fatigue each year. This results in an estimated 1,550*deaths*, 71,000 injuries, and \$12.5 billion in monetary losses [76]. The use of wearable headbands for drowsiness detection is therefore applicable on a wider scale than surface mining alone.

# Chapter 2

## System Description

This chapter describes the instruments and apparatus used for the data collection, we have described our experimental method for data collection, design of the classifiers, and evaluation metrics, the various methods used for classification and characterization of drowsiness. In this chapter we have also classified blinks which have been used previously for drowsiness detection. we have described the algorithm used by us for Blink characterization and how useful we found it to be.

### 2.1 Data collection

We used the MUSE brain sensing headband for data collection. MUSE has 7 sensors: 2 on the forehead, 3 reference sensors and 2 behind the ears. We used only the EEG data collected from one of the forehead sensors for our analysis. EEG data is sampled at 220 Hz. To emulate driving conditions, an in-lab driving simulator was used in during the data collection. The use of a simulator provides us a safe and controlled setting to carry out our experiments involving drowsy subjects.

Moreover, simulators have been shown to create driving environments that are similar to real driving conditions [8, 77, 78, 79]. The driving simulator that we have assembled consists of the following components: (i) a GTA-F Chassis from GTR that serves as a base frame for all the components, (ii) a Logitech G 27 Console that provides steering wheel, braking



Figure 2.1: Subject wearing a MUSE headband during data collection. The subject is shown operating a driving simulator.

system and standard shifter, (iii) three 24 inches monitors that provide a wide view of the simulation rendering, (iv) a vibration generation system and (v) the EuroTruck Simulation Software. Figure 2.1 shows the simulator setup.

We have collected data from 23 subjects in both *fresh* and *drowsy* states for a duration of 1 hour each. Data collection in the *fresh* state was performed in the morning hours of 8 to 11 AM, after ensuring that the subjects have had normal sleep of at least 6 to 8 hours. Bright lighting was maintained in the room and the subject was allowed to talk while being seated.

Data collection in the *drowsy* state was performed between the hours of 11 PM and 3 AM on subjects that have been awake for at least 18 hours and have not taken caffeine products the entire day. For this data collection, only a dim lighting was maintained in the room to emulated night time driving condition. The subject was left alone in the room and seated on the driving simulator for the entire duration. Facial and hand movements were allowed,

but no conversations.

## 2.2 Feature selection

A spectral analysis of EEG signals is known to be able to detect onset of drowsiness [75, 80, 81]. EEG signals are typically classified into various frequency bands, including the delta band (0.5 – 4 Hz), the theta band (4 - 8 Hz), the alpha band (8 - 13 Hz), and the beta band (13 - 25 Hz). Each of these bands are associated with certain types of activity. For example, beta frequency band is associated with alertness and focus. The alpha band is associated with relaxation. The delta and theta bands have been associated with drowsiness and sleep [80, 81].

More specifically, a decrease in the power changes in the alpha frequency band and an increase in the theta frequency band has been linked to drowsiness [8]. Therefore, one commonly pursued technique is to compute the spectral power in each of these frequency bands and design threshold that can identify onset of drowsiness. However, previous studies have also documented the difficulty in designing such thresholds which result in poor accuracy [82], [74]. Therefore, in our analysis, we have used a support vector machine with a large set of features that are computed as follows.

We first compute a Fast Fourier Transform on the EEG signal using a Hanning window of 256 points and slide it by 220 samples each. Note that the sampling frequency is 220 Hz and thus this produces an FFT output every 1 second. The frequency resolution is  $220/256$ , i.e., approximately 0.85Hz and ranges from 0 to 110Hz. Thus, for each second we obtained a spectral power for each frequency band ranging from 0 to 110 Hz in increments of 0.85Hz. We used this to compute the following features (shown in Table 2.1) in every second of the EEG data. Thus, for each subject we obtained 3600 epochs of data in a fresh state and 3600 epochs of data in a drowsy state. Each epoch contains 12 attributes as listed in Table 2.1.

Let  $|\alpha|$  denote the mean power of the alpha frequency band (8Hz - 13Hz). Let  $|\beta|$  denote the mean power of the beta frequency band (13Hz - 30Hz). Let  $|\theta|$  denote the mean power of the theta frequency band (4Hz - 8Hz). Let  $|\delta|$  denote the mean power of the delta frequency

band (0.85Hz - 4Hz). Let  $|\gamma|$  denote the mean power of the gamma frequency band (31Hz - 50Hz). Let  $|\phi|$  denote the mean power of all frequency bands (0.85Hz - 110Hz).

Table 2.1: List of features

No.	Feature	No.	Feature
1	$ \delta $	7	$ \theta $
2	$ \alpha $	8	$\frac{ \theta }{ \beta }$
3	$\frac{ \delta }{ \theta }$	9	$\frac{ \theta }{ \alpha }$
4	$\frac{ \delta }{ \beta }$	10	$\frac{ \delta }{ \phi }$
5	$\frac{ \delta }{ \alpha }$	11	$\frac{ \delta }{ \phi }$
6	$\frac{ \delta }{( \theta + \beta + \alpha + \gamma )}$	12	$\frac{ \delta }{( \theta + \beta + \alpha + \gamma )}$

## 2.3 Classification approaches

We trained 2 classifiers to test the drowsiness detection system: Linear Discriminant Analysis (LDA) and Support Vector Machines (SVM).

### 2.3.1 Linear Discriminant Analysis

Linear Discriminant Analysis (LDA) is a dimensionality reduction and classification method originally developed in 1936 by R. A. Fisher[83]. It is simple and robust. Models produced using LDA usually have accuracy as good as of more complex methods. It is a widely used technique for machine learning. The goal of LDA classification technique is to find a set of linear combination of variables that can clearly separate 2 or more classes (by using nearest neighbors approach).

A simple LDA classifier can be constructed for a 2 class problem. A LDA classifier tries to project the given data on a line (in higher dimensions) or a hyper-plane such that they are separable.

Let  $X$  be a data matrix of  $M$  samples in  $N$  dimensions. Let the number of unique classes in which the  $M$  samples can be divided be  $C$ . LDA weight vector project  $X$  (with  $n$  dimensions) to  $Y$  with  $n-1$  dimensions such that they are linearly separable. If  $n = 2$  (a binary classification problem), then reduced dimensions are of 1 dimensions. LDA can be summerized in the following steps:

1. Generate  $D$ -dimensional mean vectors for the different classes from the dataset.
2. Generate the scatter matrices(in-between class scatter ( $S_b$ ) and within-class scatter ( $S_w$ ))
3. Generate the Eigenvectors ( $e_1, e_2, \dots, e_D$ ) and relevant Eigenvalues ( $\lambda_1, \lambda_2, \dots, \lambda_D$ ) for the scatter matrices.
4. Sort the Eigenvectors in order of decreasing eigenvalues to choose  $K$  Eigenvectors of largest Eigenvalues and form a  $K * D$  dimensional matrix  $W$ .
5. Use the  $W$  matrix to transform the samples onto the new subspace. (as per equation

$$Y = W^T X \quad (2.1)$$

(where  $X$  is a  $N * D$ -dimensional matrix of the  $N$  samples, which are transformed  $N * K$ -dimensional as  $Y$  samples in the new subspace).

We have used LDA in MATLAB programming environment. It inherently support multi-class classification inside LDA [84].

### 2.3.2 Support Vector Machines

In this subsection, we talk about a popular classification technique called Support Vector Machines (SVM). SVMs were originally introduced by Vapnik in 1995 [85]. SVM is a supervised machine learning classification technique which constructs a hyperplane or a set of hyperplanes in a multi-dimension space to achieve maximum separation between the classes. Larger the separation between classes lower is the generalization error of classifier.

The value of weight vector  $w$  is found using advanced optimization algorithms. The non linear classifier applies kernel trick[86] to maximum-margin hyperplanes[87]. The original problem may be stated in a finite dimensional space, but many times the sets to discriminate are not linearly separable in that space. Therefore, the original finite-dimensional space is mapped into a much higher-dimensional space, which makes the separation easier in that space. The mappings used by SVM schemes are designed so that dot products may be computed easily in terms of the variables in the original space. This is achieved by defining them in terms of a kernel function as appropriate. This also helps in reducing the workload. The hyperplanes in the higher-dimensional space are set of points whose dot product with a vector in that space is constant. With this choice of a hyperplane, the points in the feature space that are mapped into the hyperplane are defined by a relation. In this way, the sum of kernels can be used to measure the relative nearness between each test point and the data points originating the sets to be discriminated.

Let us assume that we have an input output set  $X, Y$  such that  $X$  is the input sample which is a collection of parameters and  $Y$  is a label. Training set could be  $(x_1, y_1), \dots, (x_n, y_n)$ . For  $x \in X$  find a  $y$  such that  $y \in Y$ . Hence we need to find a function  $f$  such that  $y = f(x, \alpha)$  where  $\alpha$  is a set of parameters of the function. It can also be written as

$$f(x, \{w, b\}) = + - (w.x + b) \text{ where } w \text{ is the weight vector and } b \text{ is the bias.}$$

We have used the Gaussian radial based function as our data was not linearly separable and polynomial kernel did not yield good results. The results of SVM with Linear, RBF and Polynomial kernels are given in the next chapter. The RBF function is given as below:

$$k(\vec{x}_i, \vec{x}_j) = \exp(-\gamma \| \vec{x}_i - \vec{x}_j \|^2), \text{ for } \gamma > 0.$$

$$\text{Sometimes parametrized using } \gamma = \frac{1}{2\sigma^2}$$

It is noteworthy that working in a higher-dimensional feature space increases the generalization error of support vector machines, although given enough samples the algorithm still performs well.

It should be noted that SVM only work for 2 class classification. SVMs are a classification technique which output class of the input feature vector and dont output the probability. One can obtain probability in this case by fitting a non linear regression classifier internally

to learned non linear hyper plane. This is taken care by libsvm [88] toolkit using which SVM was implemented in Matlab.

At each second, for the feature vector of unknown class (and of length 12), the classification output and its associated probability is obtained. Support Vector Machine classifier available in libsvm [88] was used.

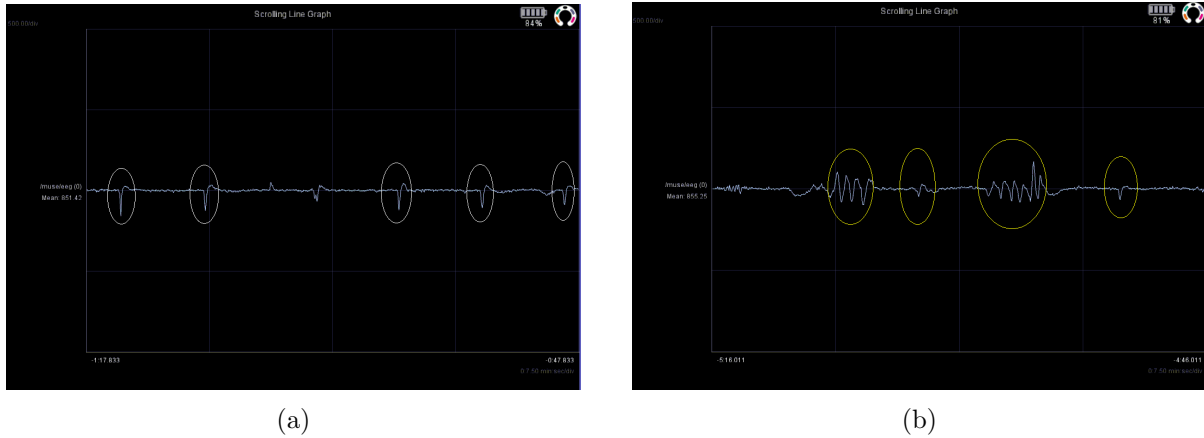


Figure 2.2: (a) Example signal patterns corresponding to a blink and (b) Example signal patterns that do not correspond to a blink

## 2.4 Experiment description

In this section, we describe the way the experiment is designed. We designed two experiments to aggregate data and test drowsiness detection and blink detection.

### 2.4.1 Per-subject training

Per-Subject training is usually the first method to evaluate the performance of an approach. Since every user is different in his own way if a separation of data is possible in their own set for randomly selected data that means that there is some possibility that the approach may work for all kinds of data. Note that for each subject, we obtained 3600 epochs of data in a fresh state and 3600 epochs of data in a drowsy state. We randomly

selected 80% of fresh data samples and 80% of drowsy data samples and use that to train the individual classifiers per subject. The remaining data, per subject, is used for evaluation. This procedure is repeated 10 times and the results are averaged, thus resulting in an 10 fold cross validation.

### 2.4.2 Cross-subject training

Cross subject training is usually done to see if the approach is universally acceptable. In this case depending on the number of people a trained classifier is created which checks if it can do a separation of unknown data(New User). If a high accuracy is achieved then we can safely say that the approach is universally acceptable. Here, we used data from 22 subjects to train a classifier and then evaluate this classifier on the remaining 1 subject. This procedure is repeated for all 23 subjects. The cross subject validation allows us to determine the applicability of previously trained classifiers on subjects whose data has not been used for training. we have tried combination of different parameters however since the results were not much different in accuracy we stick-ed with the default parameters.

### 2.4.3 Metrics

We computed the precision ( $p_r$ ), recall ( $r_c$ ) and overall accuracy ( $z$ ) in detecting drowsiness. Let  $t_p$  denote true positives,  $t_n$  denote true negatives,  $f_p$  denote false positives and  $f_n$  denote false negatives. Recall is defined as the percentage of drowsy samples that are correctly classified as drowsy.

Precision captures the impact of false predictions.

$$r_c = \frac{t_p}{t_p + f_p} \quad (2.2)$$

The overall accuracy is given as follows.

$$z = \frac{t_p + t_n}{t_p + f_p + t_n + f_n} \quad (2.3)$$

## 2.5 Blink characteristics

EEG signals obtained from MUSE can also be easily used to identify blink characteristics. Figure 2.2(a) shows the signals corresponding to the times that a subject blinks. As seen in the figure, blinks appear as a sharp decrease in amplitude followed by a sharp rise in amplitude, before returning to the steady state. We used this signature pattern to identify occurrence of blinks and the duration of each blink. Our algorithm is shown in Algorithm 1 and is characterized by the following parameters: (i) minimum downward slope ( $\lambda_d$ ), minimum rising slope ( $\lambda_r$ ), minimum time for fall ( $\delta_d$ ), minimum time for rise ( $\delta_r$ ), minimum percentage change in amplitude during downward slope ( $a_d$ ) and maximum window size ( $w_s$ ). Over each window of size  $w_s$ , We checked for the occurrence of the blink pattern. If such a pattern is found, We move the window to the end of the blink which is set to the time at which the amplitude returns to the starting value. If such a pattern is not found, we move the window by 1 sample.

---

**Algorithm 1** Blink detection algorithm

---

```

1: procedure BLINK-DETECTION
2:   repeat
3:      $t_s = t$  (start time)
4:     let  $y_s$  denote start amplitude
5:     let  $t_d$  denote time of lowest amplitude ( $y_d$ ) in  $[t, t + w_s]$ 
6:     let  $t_r$  denote time of highest amplitude ( $y_r$ ) in  $[t, t + w_s]$ 
7:     if  $((\frac{y_d - y_s}{t_d - t_s} > \lambda_d) \wedge (\frac{y_r - y_d}{t_r - t_d} > \lambda_r) \wedge (t_d - t_s > \delta_d) \wedge (t_r - t_d > \delta_r) \wedge (\frac{y_s - y_d}{y_s} > a_d))$  then
8:       Blink detected
9:       let  $t_e$  denote time instant greater than  $t_r$  when amplitude equals  $y_s$ 
10:       $t = t + t_e$ 
11:     else
12:        $t = t + 1$ 
13:     end if
14:   until end of stream
15: end procedure

```

---

Note that by this technique, the starting point for a blink will always be at the start of a window. We also checked for the fact that the rise in amplitude is followed by a fall and that the highest amplitude is larger than the starting value. This algorithm is able to eliminate signals that do not match the specification for a *blink* such as low downward and upward

slope and lower fall in amplitude during the downward sloping phase. some examples of signals that do not correspond to a *blink* are shown in Figure 2.2(b).

Table 2.2: Parameters for Blink Detection Algorithm

Parameter	Value
$\delta_d$	1.0
$\delta_r$	1.5
$\lambda_d$	0.09 sec
$\lambda_r$	0.09 sec
$a_d$	6

The specific parameters that we have chosen in our implementation are listed in Table 2.2. We verified our algorithm by manually noting down the occurrence of blinks in data from 2 subjects in fresh and drowsy states, and comparing with the output of our algorithm. Using our simple algorithm, We are able to detect  $x\%$  of blinks that occur with a  $y\%$  false positive rate.

We then used this algorithm to compute the blink characteristics for each subject in the fresh and drowsy states as follows. We divide the data for each subject into epochs of 1 minute. In each minute, we compute the average number of blinks and the average duration of a blink. For each subject, we thus obtain 60 epochs of this feature set in the state and 60 epochs in the drowsy state. We then use this data to train an SVM classifier as described in Section 2.3.

Note that we have not used a PERCLOS based approach for utilizing the blink data because it is not possible to determine 80% eye closure using the output from EEG sensors.

# Chapter 3

## Performance Analysis

In this chapter, we discuss the implementation details of this work and systematically evaluate the performance of the system. We look at 2 classification techniques and look at their results. We also compare the spectral analysis with blink analysis. We also look at the performance of the system based on temporal aggregation. Results of spectral analysis with LDA and SVM are shown and compared with Blink based techniques in this chapter.

### 3.1 Parameter and Kernel Decision

In the previous chapter we had described that we wanted to evaluate the performance of SVM using the various kernel and parameter. We wanted to check which kernel is best suited to characterize the data properly. The performance of different kernels can be seen in table 3.1.

It is indeed evident that the RBF kernel performs the best for the classification of our data. Apart from using different kernels we have also tried to evaluate different parameter

Table 3.1: Accuracy of Kernels of SVM

<b>RBF</b>	<b>Polynomial</b>	<b>Linear</b>
74%	54%	64%

Table 3.2: Accuracy of Parameter of RBF SVM Kernel

<b>Gamma and c</b>	<b>0.1</b>	<b>1</b>	<b>10</b>
0.01	71.70 %	74.54%	75.35%
0.067	74.29 %	75.42%	75.73%
0.1	74.18 %	75.44%	75.48%
1	69.67 %	72.02%	72.02%

options. The accuracy of 10 fold cross validation for different parameter combination is given in table 3.2.

Since the accuracy of 10 fold cross validation for default parameters was 75.45% and the maximum difference with the parameter combination giving the highest accuracy was in fractions we decided to use the default parameters in our setup.

## 3.2 Blink Detection

In this section we have described the performance analysis of the Blink Detection based Drowsiness detection. We used the labeled data generated with the algorithm as described in the previous section as a parameter for Drowsiness detection. The idea behind this approach is to see if the blink duration or frequency has any effect on Drowsiness detection.

### 3.2.1 Subject Based Analysis

In this section, we have described the performance analysis of Blink Detection for Drowsiness detection. First, we consider a per-subject analysis, where the training and testing data belong to the same subject. The classifiers are tested using a 10 fold cross validation, i.e., 10 different set of training and test data are randomly picked for each subject in a 4 : 1 train:test ratio. A bar graph of the classification accuracy is shown in Figure 3.1(a) using LDA classifier respectively.

### 3.2.2 Cross Subject Validation

Next, we show the results of cross subject validation using both classifiers in Figure 3.1(b). The cross-subject validation is carried out with a one subject left out strategy. In other words, we trained the classifier using data from 22 subjects and test on the remaining one subject. We repeat this 23 times (once for each subject). Cross-subject validation is important to ascertain that the system can be used with previously trained classifiers on *unseen* subjects. As seen in Figure 3.1(b), since the accuracy is too low there is no reason to apply SVM also.

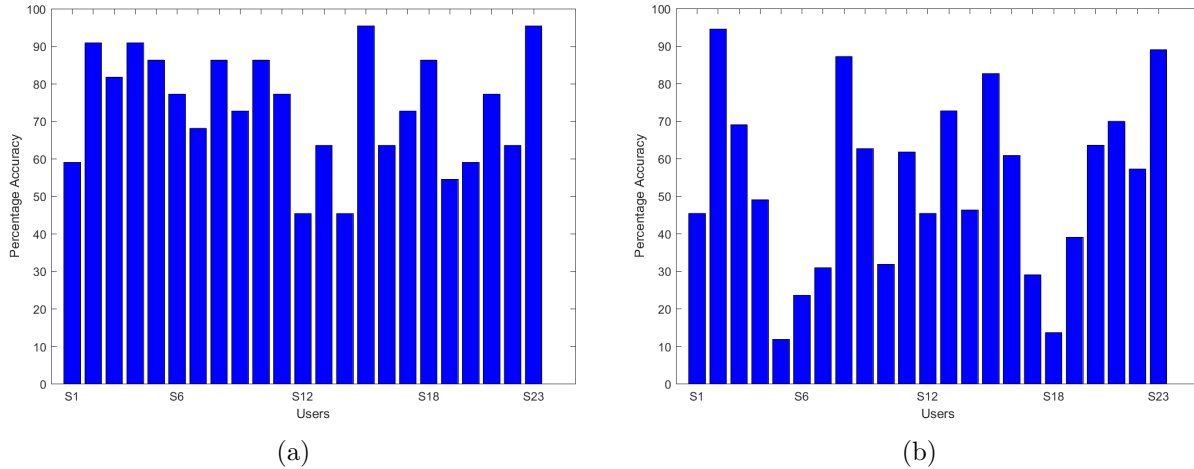


Figure 3.1: (a) Bar graph of classification accuracy per subject with LDA classifier using Blink data and (b) Bar graph of classification accuracy across subject with LDA classifier. The classifiers are tested using an 10-fold cross validation for per subject and 22-fold cross validation for across subject, i.e., 10 different set of training and test data are randomly picked for each subject in a 4 : 1 train:test ratio for the per subject and 22 subjects for training and the remaining one subject for testing. The average results per subject are reported.

## 3.3 Spectral Based Drowsiness Detection

In this section, we have described the performance analysis of the 12 parameters generated from the Spectral data for Drowsiness detection.

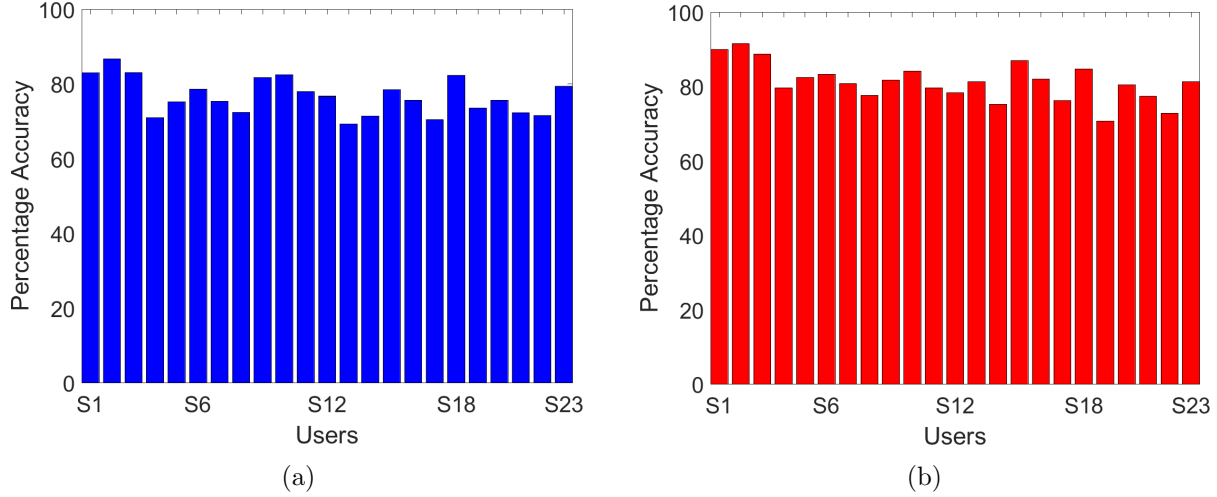


Figure 3.2: (a) Bar graph of classification accuracy per subject with LDA classifier and (b) Bar graph of classification accuracy per subject with SVM classifier. The classifiers are tested using an 10-fold cross validation, i.e., 10 different set of training and test data are randomly picked for each subject in a 4 : 1 train:test ratio. The average results per subject are reported.

### 3.3.1 Subject based analysis

In this section, we described the performance analysis of our system. First, we consider a per-subject analysis, where the training and testing data belong to the same subject. The classifiers are tested using an 10-fold cross validation, i.e., 10 different set of training and test data are randomly picked for each subject in a 4 : 1 train:test ratio. A bar graph of the classification accuracy is shown in Figure 3.2(a) and Figure 3.2(b) using LDA and SVM classifiers respectively.

These results are more succinctly represented in Figure 3.3, where we show the precision, recall and accuracy of the spectral analysis method using LDA and SVM classifiers on a per-subject basis. The box plot captures the variations across the 23 different subjects. We observe that the median accuracy is 76% for LDA classifier and 81% for the SVM classifier. A further breakdown of the accuracy reveals that the precision is higher than the recall (sensitivity). Thus the system is more tolerant to false positives in drowsiness detection.

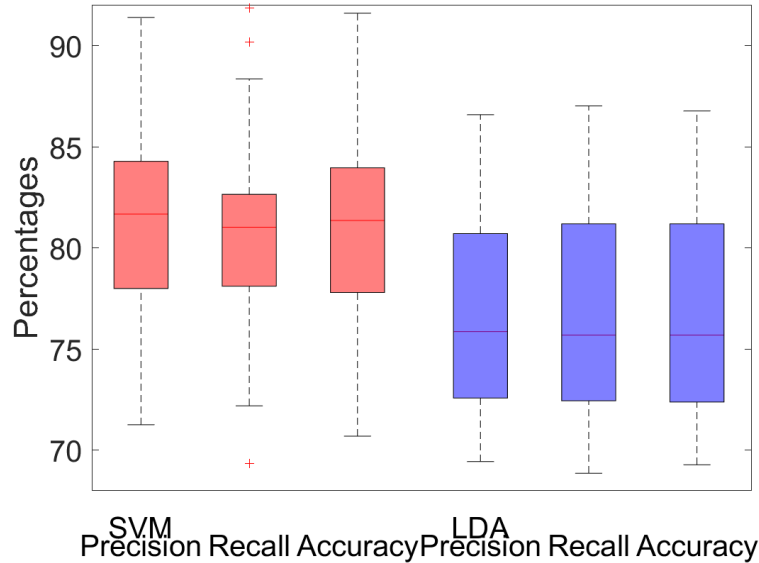


Figure 3.3: Comparison of precision, recall and accuracy on a per-subject basis using SVM and LDA classifiers with spectral features of EEG signals. The classifiers are tested using an 10-fold cross validation, i.e., 10 different set of training and test data are randomly picked for each subject in a 4 : 1 train:test ratio.

### 3.3.2 Cross Subject Validation

Next, we show the results of cross subject validation using both classifiers in Figure 3.4. The cross-subject validation is carried out with a one subject left out strategy. In other words, we trained the classifier using data from 22 subjects and test on the remaining one subject. We repeat this 23 times (once for each subject). Cross-subject validation is important to ascertain that the system can be used with previously trained classifiers on *unseen* subjects. As seen in Figure 3.4, the median accuracy using LDA is 68% and SVM is 74%.

Note that the accuracy of our system is computed using training and test samples that are drawn from *fresh* and *drowsy* data set of each subject. Under this scenario, it is hard to ascertain that each sample drawn from a drowsy data set corresponds to a unique drowsy signature.

Levels of drowsiness may vary over time. Hence, our expectation from a good classifier

### 3.3. SPECTRAL BASED DROWSINESS DETECTION PERFORMANCE ANALYSIS

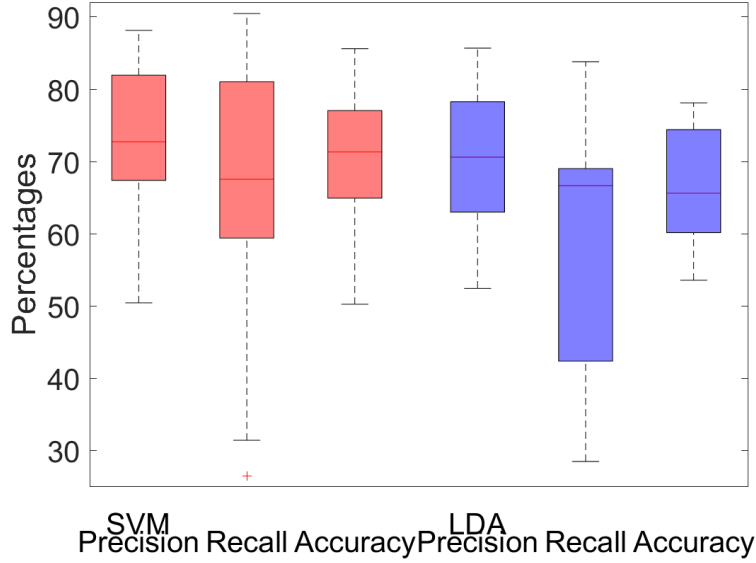


Figure 3.4: Comparison of precision, recall and accuracy in a cross subject validation using SVM and LDA classifiers with spectral features of EEG signals. We trained the classifier using data from 22 subjects and test on the remaining one subject. The box plot captures the variations in classification performance across the 23 subjects.

is that a significant majority of samples in the drowsy state are classified as *drowsy*. The results of our analysis match this expectation. The fact that accuracy is high even in cross subject validation shows that the system can be used for real-time drowsiness detection using previously trained classifiers.

#### 3.3.3 Temporal aggregation

We now study if temporal aggregation of the classifier outputs can further improve the accuracy. To do so, we aggregated the classifier outputs over different intervals of the test data by classifying the data as *fresh* if greater than 50% of the samples in that interval are classified as fresh and classifying the data as *drowsy* if greater than 50% of the samples in that minute are classified as drowsy. We have considered intervals of 1, 3 and 5 minutes.

This idea is motivated by the fact that in real-time one does not expect an output for fresh

### 3.3. SPECTRAL BASED DROWSINESS DETECTION PERFORMANCE ANALYSIS

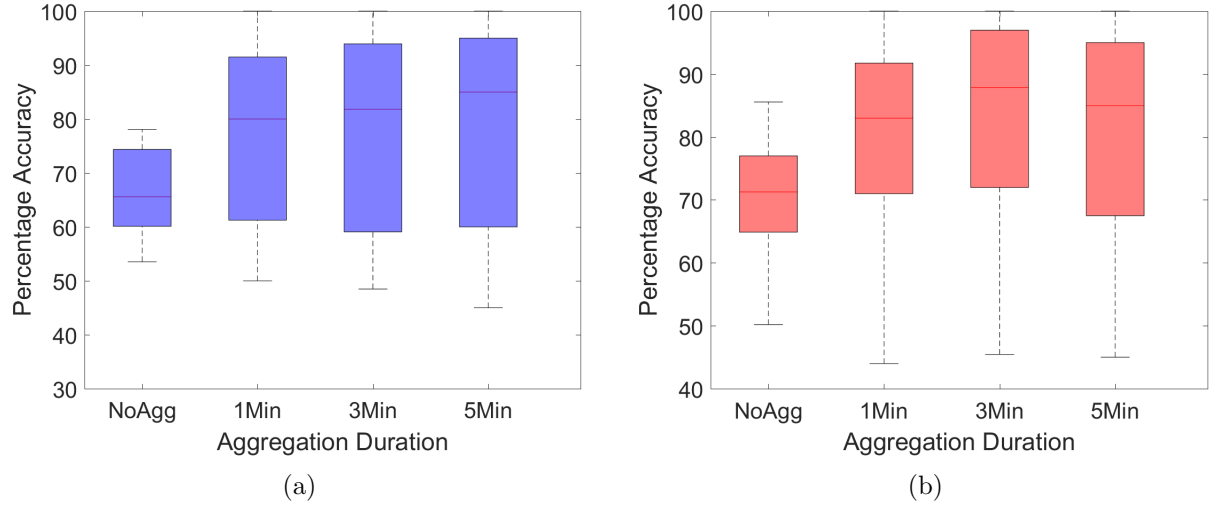


Figure 3.5: (a) Impact of temporal aggregation on accuracy with LDA classifier and (b) Impact of temporal aggregation on accuracy with SVM classifier

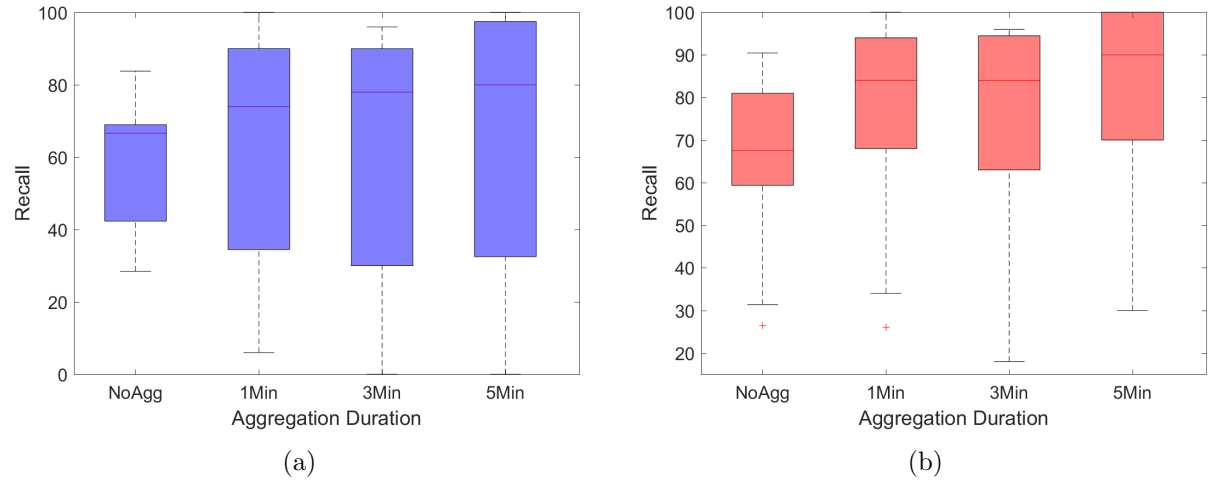


Figure 3.6: (a) Impact of temporal aggregation on sensitivity (recall) of drowsiness detection with LDA classifier and (b) Impact of temporal aggregation on sensitivity (recall) of drowsiness detection with SVM classifier

### 3.3. SPECTRAL BASED DROWSINESS DETECTION PERFORMANCE ANALYSIS

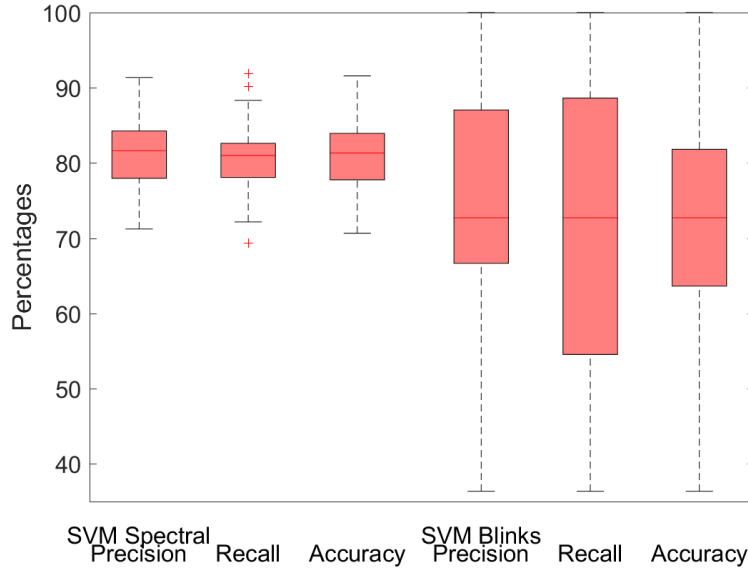


Figure 3.7: Comparison of precision, recall and accuracy on a per-subject basis with a blink based analysis and spectral analysis. An SVM classifier is used for both. The classifiers are tested using an 10-fold cross validation, i.e., 10 different set of training and test data are randomly picked for each subject in a 4 : 1 train:test ratio.

or drowsy states every second. Instead, a temporal aggregation of classifier outputs would be more meaningful. The results of such temporal aggregation are shown in Figure 3.5(a) and Figure 3.5(b) for LDA and SVM respectively. We observed that the percentage accuracy improves with temporal aggregation. In Figure 3.6(a) and Figure 3.6(b), we show the impact of aggregation on the sensitivity (recall) in terms of drowsiness detection. we noticed a steady improvement here also.

Finally, we characterize the accuracy of the system using blink characteristics with an SVM classifier. We show the precision, recall and accuracy of the blink analysis method on a per-subject basis in Figure 3.7. The performance of cross subject validation is shown in Figure 3.8. In comparison with spectral analysis, we observed that the median accuracy is lower. We also observed a large variation in results across different subjects with accuracy of under 10% at the lower end. Thus, our results show that spectral analysis of the EEG signal is a more reliable indicator of drowsiness, especially when inter-person variations are considered.

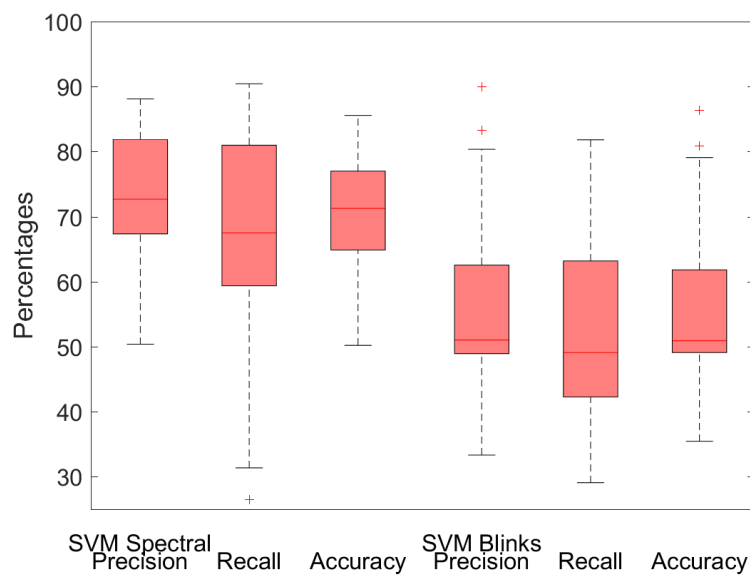


Figure 3.8: Comparison of precision, recall and accuracy in cross-subject validation with a blink based analysis and spectral analysis. An SVM classifier is used for both. We trained the classifiers using data from 22 subjects and test on the remaining one subject. The box plot captures the variations in classification performance across the 23 subjects.

# Chapter 4

## Conclusion and Future work

This section concludes the thesis by providing conclusions and indicates directions for future work.

### 4.1 Conclusions

In this research, we have demonstrated the feasibility of using commercially available, lightweight, wearable brain sensing headband (MUSE) for detecting drowsiness of drivers in real-time. Using spectral features of the EEG signal We were able to achieve 74% accuracy in cross subject validation with SVM and 68% accuracy in cross subject validation with LDA.

Using temporal aggregation of the classifier output, we were able to improve the accuracy to 90%. We also extracted blink duration parameters from the EEG signal and used that to detect drowsiness. However, the accuracy using blink parameters was found to be lower than spectral analysis. It is hence proven that spectral analysis of EEG signals is better than Blink based drowsiness detection. We also found that even though LDA was much faster as compared to SVM, SVM was performing better as compared to LDA.

We would like to build upon these results and collect data over a longer term using the wearable EEG sensors in an actual vehicular setting inside surface mines. This data can be used to understand the issue of driver fatigue in more detail and help in designing better

work hours and shifts. Drowsiness data can also be used to develop personalized work shifts for drivers based on their specific pattern of drowsiness. We also intend to explore real time warning systems that use a combination of blink analysis and spectral data for more accurate and timely warnings. We would also like to explore appropriate response strategies upon detection of drowsiness in drivers.

## 4.2 Future work

It is a known fact that EEG is one of the best technique for drowsiness detection however it is not without flaws. Drowsiness is a state which can either convert into sleep state or go towards fresh state. As there is no method to check these states or states changes there will be requirement of introducing corrections in these conditions. In future we hope that these states can be properly be checked and defined.

Another source of error in data collected can be introduced during the process of data collection itself. the data collection depends on the type and steadiness of sensors which produces robust data. For the moment we have depended on sensors which required steady conditions during data collection process. We recommend that improved, better and multiple types of sensor sets may be used to introduce redundancies needed for improving the data collection process. We are sure that will improve accuracies further. We hope that in the future such better sensors and systems with multiple sensors which is lightweight will be developed.

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