ABSTRACT

Title of Thesis:	QUANTITATIVE AND QUALITATIVE TRADE-OFF ANALYSIS OF DROWSY DRIVER DETECTION METHODS
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Drowsy driving impairs motorists' ability to operate vehicles safely, endangering both the drivers and other people on the road. The purpose of the project is to find the most effective wearable device to detect drowsiness. Existing research has demonstrated several options for drowsiness detection, such as electroencephalogram (EEG) brain wave measurement, eye tracking, head motions, and lane deviations. However, there are no detailed trade-off analyses for the cost, accuracy, detection time, and ergonomics of these methods. We chose to use two different EEG headsets: NeuroSky Mindwave Mobile (single-electrode) and Emotiv EPOC (14-electrode). We also tested a camera and gyroscope-accelerometer device. We can successfully determine drowsiness after five minutes of training using both single and multi-electrode EEGs. Devices were evaluated using the following criteria: time needed to achieve accurate reading, accuracy of prediction, rate of false positives vs. false negatives, and ergonomics and portability. This research will help improve detection devices, and reduce the number of future accidents due to drowsy driving.

QUANTITATIVE AND QUALITATIVE TRADE-OFF ANALYSIS OF DROWSY DRIVER DETECTION METHODS:

SINGLE ELECTRODE WEARABLE EEG DEVICE, MULTI-ELECTRODE WEARABLE EEG DEVICE, AND HEAD-MOUNTED GYROSCOPE

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List of Abbreviations

ECoG - Electrocorticography

EEG - Electroencephalography

EOG - Electro-olfactogram

MEMS - Microelectromechanical systems

MRI - Magnetic resonance imaging

PCA - Principal component analysis

PSD - Power spectral density

REM - Rapid eye-movement

VOR - Vestibulo-ocular reflex

FFT - Fast Fourier Transform

DFT - Discrete Fourier Transform

Chapter 1: Introduction

1.1 Research Problem

According to Charles Czeisler, Professor of Sleep Medicine, 24 hours without sleep, or a week of sleeping four or five hours a night induces an impairment equivalent to a blood alcohol level of 0.1% (Czeisler, 2006). Researchers have estimated that up to twenty percent of serious crashes in the United States are related to sleepy driving (Horne, 2000). Other researchers have found that drowsy driving is the principal cause of more than 100,000 automobile crashes with 1,500 fatalities each year (NHTSA, 2003). The issue is comparable in scope to distracted driving (e.g., texting, using the phone, adjusting the radio) which results in 3,000 fatalities per year (National Center for Statistics and Analysis, 2013) or drunk driving which leads to 10,000 traffic fatalities a year (CDC, 2016). Given that substance use by the driver is easier to detect than driver drowsiness after a crash, there is reason to believe the harm from drowsiness is underestimated. Like texters and drunk drivers, drowsy drivers are typically unaware of their level of impairment (Reyner & Home, 1998). Social pressures give incentives for drivers to be aware of and self-regulate their drunk driving or texting. However, drowsy driving does not carry a significant social stigma. These problems surrounding drowsy driving can be mitigated by monitoring the alertness of drivers and informing them when they become too tired to drive safely.

1.2 Purpose

Existing alerting solutions may be built into the car, such as Saab's built-in infrared cameras (Dong, Hu, Uchimura, & Murayama, 2011). Other researchers have used wearable headsets that use other types of detection to determine drowsiness, such as the Vigo headset (Grush, 2013). The limitations to existing solutions are cost and lack of accuracy. In-car systems are expensive and both in-car and wearable devices suffer from lack of accuracy. There is no comprehensive comparison to see how different trade-offs such as cost, accuracy, time delay in detection, and comfort affects the choice of a device.

1.3 Research Questions

To fill these knowledge gaps, our research goals were: 1) implement accurate drowsiness detection devices on several wearable devices, and 2) compare the cost trade-offs to determine the best device for cost-efficient portable drowsiness detection. Our research questions were: 1) How can we detect drowsiness as cheaply and accurately as possible? 2) What are the trade-offs between price, convenience, and accuracy?

1.4 Method Framework

We used four major hardware devices: NeuroSky Mindware Mobile headset (single forehead electrode, $130), Emotiv Epoc headset (14-electrode device, $700), Modified Microsoft LifeCam HD-6000 (eye movement tracking, $40), and head-mounted MPU6050 gyroscope (head-nod detection, $10). Existing research has demonstrated that changes in brainwave activity, measured in volts using electroencephalography (EEG) can be used to detect drowsiness. Different frequency bands: alpha, beta, delta, or theta waves, correspond to different levels of alertness (Lee & Lo, 2000). We use this approach with the NeuroSky and Emotiv headsets. In order to collect data, we collected data in three scenarios, 1) when awake normally, 2) when nodding off in a dark environment with eyes periodically closed, and 3) with concentrated brain activity, such as playing an N-Back memory game. We then distinguished the drowsy samples from the other samples using MATLAB. Other methods for drowsiness detection, such as percentage of time the eyes are closed (PERCLOS) and and head nods both correspond to drowsiness. The vestibulo-ocular reflex (VOR) checks how closely an eye tracks a still object while the head is moving, such as when sitting in a moving car, and is a minute change that also corresponds to drowsiness. We combined the gyroscope and camera to detect these changes.

1.5 Significance of Findings

We successfully showed that the NeuroSky Mindwave Mobile, a single-electrode EEG consumer device, can distinguish between drowsy and alert states after collecting data for three minutes. We could also distinguish drowsy and alert states with the Emotiv (14-electrode) device after two minutes but were unable to find that using electrodes on different parts of the head improved this value. We concluded that because of the additional expense and saline pads used on the Emotiv, it would be more effective to use the NeuroSky. We found that the LifeCam and gyroscope were not effective for VOR and drowsiness detection, and head nods were fairly inaccurate. The most effective device would be an improved single-electrode device with dry electrodes that would be less obtrusive to wear. More research is needed to determine if accuracy and time needed can be increased for these devices, and to create an improved device that can be worn unobtrusively. These findings are important for knowing the trade-offs to creating a more widely used wearable drowsy driving alerting device, and ultimately reducing the number of accidents to due drowsy driving.

Chapter 2: Literature Review

2.1 Sleep Deprivation and Cognitive Ability

Sleep deprivation has been shown to disrupt frontal brain regions as well as cause lapses in attention (Renn & Cote, 2013). In a study by Renn and Cote (2013), sleep deprived individuals were shown to have slower responses, increased inaccuracies, attentional impairments, and had more false alarms when taking various response inhibition tests as their amounts of sleep decreased. Furthermore, they found that sleep deprived people were not able to habituate to error as easily in comparison to those who were well-rested. They therefore concluded that loss of sleep caused impaired frontal cortex function, which led to increased errors and reduced attention.

2.2 Sleep and the Brain

Sleep progresses by alternating between two states: non-REM and REM (rapid eye movement) sleep. Non-REM sleep can be further broken down into four stages that include drowsiness, light sleep, and deep or slow-wave sleep (Acharya U., Faust, Kannathal, Chua, & Laxminarayan, 2005). Drowsiness detection aims to identify onset of the first stage of non-REM sleep (N1), where the individual begins to shift from a state of wakefulness to the first stage of sleep proper (N2, stage 2 sleep). When fatigued, a person can experience “microsleep” cycles (brief lapses into stage 2 sleep) followed by intermittent periods of arousal (Lal & Craig, 2002).This wavering of an individual’s alertness before falling asleep makes it difficult to pinpoint the exact moment of sleep onset. However there are some behavioral changes commonly associated with the wake-to-sleep transition, including brief continuation of a simple behavioral task before cessation, lack of visual response, increased delay in auditory response, and difficulty recalling short-term memories (Carskadon & Dement, 2011). These changes allow drowsy drivers to continue driving while their responses to stimuli begin to fade, sometimes without even realizing they are falling asleep.

In addition to behavioral differences, there are also changes in brain activity as an individual progresses through the various stages of sleep. These can be observed by measuring the change in electrical activity of neurons across the scalp. These measurements can be categorized into: delta (1–4 Hz), theta (4–8 Hz), alpha (8–14 Hz), and beta (15–30 Hz) waves (Brown, Basheer, McKenna, Strecker, & McCarley, 2012).

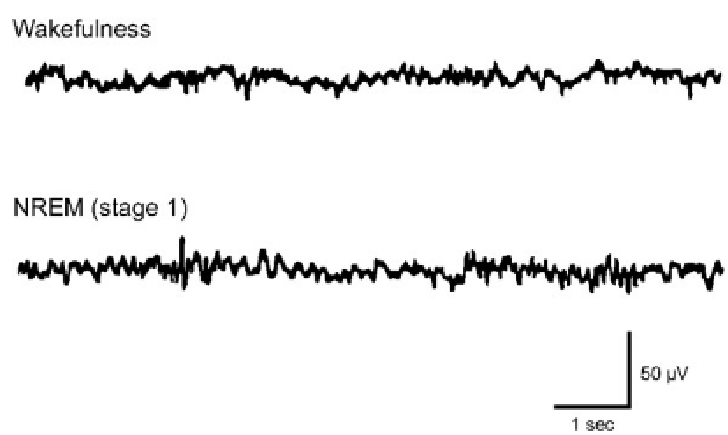

Figure 2.2.1: Electroencephalographic recordings of a subject in a wakeful state and in stage 1 sleep. Picture taken from Brown, Basheer, McKenna, Strecker, & McCarley (2012)

Wakefulness is characterized by low-amplitude/high-frequency activity. In stage 1 sleep, the frequency begins to slow (Brown, Basheer, McKenna, Strecker, & McCarley, 2012). Generally, beta waves are associated with alertness and focus, alpha waves with awareness and relaxation, theta with light sleep, and delta with deep sleep (Acharya U., Faust, Kannathal, Chua, & Laxminarayan, 2005).

2.3 Effects of Stimuli on Alertness

There are a variety of ways to try to keep a person alert, such as by exposing them to various stimuli. These methods can be categorized into auditory, olfactory, and tactile. Studies have evaluated existing methods and their effectiveness in keeping the brain aware (Gershon, Ronen, Oron-Gilad, & Shinar, 2009; Mann, 2011; Raudenbush, Grayhem, Sears, & Wilson, 2009).

Using visual methods to maintain alertness when driving can be somewhat ineffective. The stimuli have to be noticeable enough to alert the driver, but cannot be overly distracting, as diverting the driver's attention from the road can be dangerous. Thus auditory approaches can be more useful for such situations where visual stimuli are difficult to incorporate. Studies have found that trivia increased alertness and safe-driving (Mann, 2011). One study tested this theory by using a trivia game that asked the driver multiple choice questions. The driver could give the answer by pressing one of three buttons. In order to make the experiment more interesting, the driver could choose from different categories of questions, such as movies, sports, cuisine, current events, and general knowledge (Gershon, Ronen, Oron-Gilad, & Shinar, 2009). In the experiment, an integrated driving simulator from Systems Technology, Inc. projected a visual display of the road onto a three-meter by three-meter screen, and cameras were used to monitor the subject. They also used an EEG with two skin electrodes from Atlas Researches Ltd. Signals to measure alertness using R wave intervals. These researchers concluded that interactive cognitive tasks had an immediate positive impact on driving alertness but that these effects dissipated quickly after the task ended. This methodology is very clear and used somewhat objective measuring techniques to come to its conclusion. It can be strengthened by testing a broader range of interactive cognitive tasks and seeing if they have similar effects. This research is significant because it suggested that trivia can be used to reduce drowsy driving automobile crashes, more so than simple alerting tones. A phone application named “Drivia” is a voice activated trivia game that has similar trivia categories and takes verbal responses “one,” “two,” or “three” to multiple choice questions which applies this concept (Mann, 2011). This can be combined with drowsiness detection to enhance driver awareness.

In addition to targeting hearing in efforts to keep drowsy drivers awake, researchers have also focused on the nose. Researchers have noted that behavioral, verbal, and EEG responses to strong trigeminal stimulants, such as peppermint and pyrimidine, are well maintained even in stage 1 sleep (Carskadon & Dement, 2011). In other research, a virtual reality driving software was used to simulate driving while participants wore a nasal cannula which delivered oxygen mixed with peppermint or cinnamon. They were then evaluated using the NASA-Task Load Index to measure the effects of the task, and were shown to have reduced perception of effort and frustration, even when unaware of the odor (Raudenbush, Grayhem, Sears, & Wilson, 2009). Other studies have found that a pleasant lavender odor significantly undermines the performance of working memory, reaction time, attention based tasks, and arithmetic reasoning (Moss, Cook, Wesnes, & Dickett, 2003). This particular methodology did not use EEG to determine the effects of such odors, but systematically controlled the administration of the odor in level doses.

Although various odorants can have a wide range of effects on an individual, conscious of their presence or not, even strong stimulants elicit significantly less response as sleep onset occurs. In one study, the pleasant smell of peppermint was not detected during stage 2 sleep, the unpleasant smell of pyrimidine was detected only occasionally, and neither were smelled in deep sleep (Carskadon & Dement, 2011). While olfaction has potential to increase alertness in drowsy drivers, as soon as the individual drifts to sleep, sense of smell can prompt very little response. Furthermore, prolonged exposure to a scent can cause olfactory fatigue, causing perception of that smell to fade with time.

While studies have shown that auditory and olfactory stimuli can increase attention in drowsy drivers, physical stimuli can also be used to alter someones brain wave activity. Researchers have found that massage therapy reduced anxiety and enhances EEG patterns of alertness (Field et al., 1996). Twenty-six adults were asked to relax in a massage chair two times a week for five weeks, and were EEG monitored on the first and last day (Field et al., 1996). Although stimuli such as massage chairs that are intended to cause relaxation rather than alertness would be counterproductive to increasing driver alertness, some sort of physical or haptic feedback such as a brief vibration of the driver's seat or steering wheel may be a useful alert. One study used seat belt vibration as a stimulant to wake sleeping drivers, but the researchers noted the importance of finding a balance of intensity between uncomfortable and too weak, while also not interfering with driving ability (Arimitsu et al., 2007).

2.4 Common Methods to Keep Drivers Awake

Many methods have been used in attempts to extend the amount of time a driver is able to remain alert and focused on the roadway. The most common of these have involved techniques or items that are readily available to drivers who unexpectedly find themselves becoming sleepy while still far from their destination. Some common methods include rolling down the window, turning up the AC, getting exercise, listening to a radio or cassette, and consumption of coffee or another caffeinated beverage (Arimitsu et al., 2007). While all of these work to an extent, they all have drawbacks as well. Rolling down the window, turning up the AC, getting exercise, and listening to music all serve to catch the person's attention and allow him or her to remain concentrated for a bit longer. However, they are all temporary measures, and fail to solve the real problem of giving a person enough energy to remain focused. Therefore they last for ten to fifteen minutes at best before the driver begins to drift to sleep again (Arimitsu et al., 2007).

Caffeine provides more of a long term solution, but it has its drawbacks as well. For instance, 200 mg of caffeine, or around 2-3 cups of coffee, can keep someone alert for up to two hours, but it takes about half an hour to start taking effect (Reyner & Horne, 2000). Because of this, it has to be taken before the person realizes that they are becoming tired or it will not be as effective at keeping them awake. Since it can be difficult to tell ahead of time when someone will be tired enough to require caffeine, it is difficult to use it as an effectual method of drowsiness prevention. Furthermore, the person who requires caffeine may not be able to access it when he or she needs it. Naps can also increase someones alertness by providing the body with a short period of needed rest. However, it may not be efficient for someone to take a nap in the middle of a trip, he or she may not be able to pull over to sleep, and they may be unwilling or in denial of their need to nap.

One method of increasing alertness that does not rely on the driver's proactivity is the use of rumble strips on the edge of a road. When rumble strips were added to the side of the Pennsylvania Turnpike, accidents there decreased by seventy percent (Hickey Jr, 1997). However, rumble strips are used mostly to discourage swerving off the side of the road, not between lanes, and their effects on reducing sleepiness are only temporary, lasting typically 2-3 minutes (Anund, Kecklund, Vadeby, Hjälmdahl, & Åkerstedt, 2008). Similarly, striped road markings placed in accident prone areas in Japan reduced drowsy driving incidents from 3-4 per month down to zero (Yamashita & Takata, 1991). While these methods are certainly effective at keeping drivers from going off the sides of roads, they are impractical to implement across the entirety of large highway systems like those found in the United States.

2.5 Existing Drowsy Driving Detection Systems

Car manufacturers including Toyota, Saab, Nissan, and Volvo have developed systems for detecting driver drowsiness, but often come in expensive technology packages bundled with a new car (Dong, Hu, Uchimura, & Murayama, 2011). These in-car systems monitor driver drowsiness through a combination of measurements including driving habits and eye movement. As an individual falls asleep, their response times to visual stimuli begin to slow, so they make fewer adjustments to stay within a lane. Some car companies such as Mercedes-Benz take advantage of this and measure steering motions and lane position as well as monitor other adjustments such as radio volume to determine the driver's level of focus. Saab uses infrared cameras to look for eye movements associated with drowsiness, such as eyelid closure or deviation of focus from the road before alerting the driver with messages or seat vibrations (Dong, Hu, Uchimura, & Murayama, 2011).

However, systems that monitor driving habits may detect drowsiness too late. By the time the car has determined that the driver has swerved out of their lane, they could have already crashed into another vehicle or off the road. Furthermore, for a short period of time right before sleep onset, an individual can continue simple behavioral tasks (Carskadon & Dement, 2011). Therefore it is possible for a sleeping driver to continue pressing a gas pedal and holding a steering wheel straight for a brief period, even though they are not alert to their surroundings. In this case, a behavior-based drowsy driving detection system may not recognize the driver is sleeping, even if their eyes are closed. Although camera-based approaches that track eye movement could potentially detect drowsiness earlier than behavior-based approaches, environmental factors such as movement, sunlight, reflections from glasses, and sunglasses can interfere with the camera's ability to accurately track eye movement (Dong, Hu, Uchimura, & Murayama, 2011).

2.6 Head Nods as a Predictor of Sleep Onset

One approach to detecting drowsiness is by monitoring head motions, specifically nods. During sleep, the body's muscles relax, including the ones in the neck holding the head upright when a driver is sitting. This causes the individual's head to nod, falling down as they lose consciousness and tilting back up in an effort to maintain the original position (May & Baldwin, 2009). Therefore by measuring head motion with a gyroscope, one can detect sleep onset. Some difficulties with this method include late detection and false alarms. By the time a driver begins to nod their head, he or she is already falling asleep and thus unfit to drive. Also, driving requires a lot of head motion to check surroundings, such as when switching lanes or turning. This could make it difficult to distinguish between the involuntary movements that occur when an individual is drowsy and the intentional motions needed for safe driving. However, this could be overcome by detecting specific head motions over a period of time, such as a head drooping significantly for a period of more than a couple seconds, or by measuring acceleration associated with involuntary head nodding but not purposeful head turning.

2.7 Eye-Tracking to Detect Drowsiness

Although environmental factors can potentially interfere with an eye-tracking camera, it is still a reliable method to detect drowsiness. In eye-tracking there are two main events to observe: eyeball movement and eyelid movement. During sleep onset, eye motion slows; the individual stops looking around as frequently and blinks last longer before the eyelids close completely (Lal & Craig, 2002). Thus by measuring the changes in frequency of blinks, length of blinks, and duration between shifts in gaze, sleep onset can be detected. However, as with head nods, by the time a driver's eyes begin to close, they are already falling asleep and therefore unfit to drive.

A more specific measurement comparing head and reflexive eye movement could predict drowsiness earlier, before the eyes begin to close. The vestibulo-ocular reflex (VOR) causes your eye to counter-rotate in response to head motions. This allows for image stabilization on the retina, so what an individual sees is still clear, even if their head is shaking. A driver's head constantly shakes due to bumps in the road, and since VOR performance has been shown to degrade significantly with fatigue, decreased performance of VOR can be used to predict drowsiness (Hirata, Nishiyama, & Kinoshita, 2009).

2.8 Measuring Alertness with Brain Waves

The established methods and theories that deal with monitoring drowsiness are related to brain wave monitoring and eye movement monitoring. Brain waves exist as electrical activity throughout the brain. A brain wave is the change in voltage from one electrode and its counterpart across the cranium (Van Deen, Van Drongelen, Yuchtman, & Suzuki, 1997). The difference in voltage arises due to a neuron “firing” or a rapid change in the spatial orientation of the ions in a neuron. The change leads to a domino effect where nearby neurons are excited and change the orientation of their ions. A single neuron firing may be impossible to detect, but the emergent behavior of thousands or millions of neurons produces meaningful electrical signals on the scalp (Malmivuo & Plonsey, 1995).

The primary method of measuring brain waves is through the use of an electroencephalograph or EEG. The EEG consists of an array of electrodes that attach to the scalp of the patient to measure the electrical activity on the surface (Ritter & Villringer, 2006). In a full laboratory EEG, the electrodes are attached in the internationally-standardized 10-20 System (Malmivuo & Plonsey, 1995).

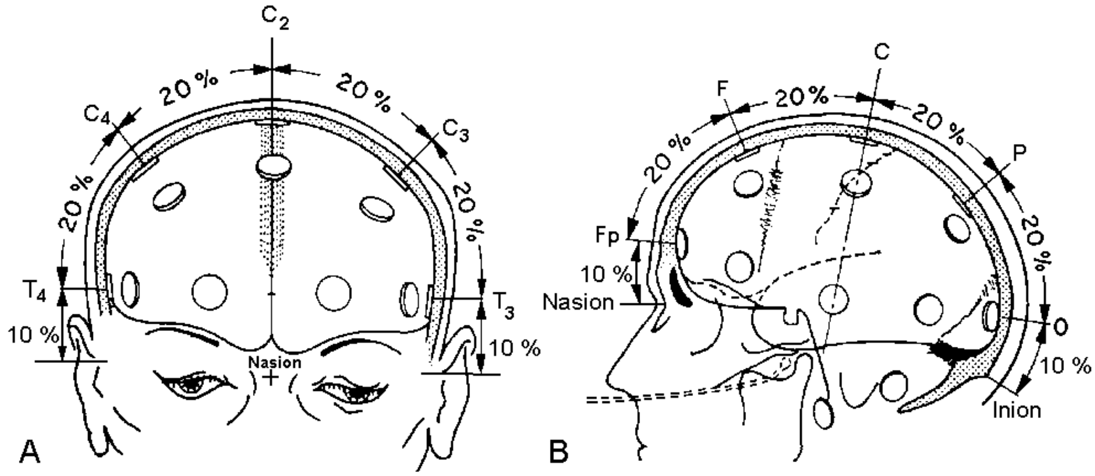

Figure 2.8.1: Diagram of electrode placement using the international 10-20 system.

Picture taken from Klem, Lüders, Jasper, & Elger, [1999].

The electrodes themselves may either be wet or dry. Conventionally, wet electrodes were used as they had a better signal impedance—defined in this paper as the resistance effect of the electrode on the amplitude of the brain wave signal (Chi et al., 2012). Wet electrodes, however, require extra preparation in the form of an adhesive, conductive AgCl gel that is applied to the scalp, which can be both inconvenient and uncomfortable (Chi et al., 2012).

Recent work has demonstrated that some dry electrodes can have a lower signal impedance than the wet electrode. One such type is the Micro-Electro-Mechanical Systems (MEMS) silicon spiked dry electrode array (Chiou et al., 2006). The signal intensity and size of the electrodes are also improved by using this dry electrode as opposed to a conventional wet electrode. The surface layer of the skin, the epidermis, can be divided into the stratum corneum and stratum germinativum. The stratum corneum is mostly dead skin cells and is not conductive while the stratum germinativum is conductive. The dry electrode pierces the stratum corneum, but does not go further in order to prevent pain or uncomfortableness to the subject (Chiou et al., 2006). Since the MEMS dry electrode is expensive and requires preparation, it may be used for laboratory testing, but not for the final product due to the inconvenience involved.

The EEG is capable of high temporal resolution within the range of a few milliseconds. This means that the EEG is able to obtain essentially immediate data to be used. However, the accuracy of the EEG is lower since it is only able to measure the normal component of the current dipoles (Ritter, & Villringer, 2006). This means that the sensors are only able to pick up the current that is directly flowing at them and not anything flowing tangential.

The EEG is also dependent upon the number of EEG channels. Electrocorticography or ECoG is considered to be a fix to the sensitivity issue. The ECoG is essentially an EEG that is directly attached to the surface of the brain. The direct attachment allows for the signal to be significantly stronger and for the noise to be weaker. However, this also makes it a highly invasive and difficult procedure that requires one to open up the scalp and directly attach electrodes to the brain (Darvas et al., 2010). Rather than relying on ECoG, it is much more common to use wet electrode caps. These are essentially the same as normal EEGs, but they have a conductive liquid/gel that allows for signal to flow better from the scalp to the electrodes (Malmivuo, & Plonsey, 1995). Another type of brain wave monitoring device is the Magnetoencephalograph or MEG. This device is able to measure the weak magnetic fields generated by the electrical activity in the brain. The temporal resolution is similar to the EEG with a range of less than one millisecond, and the accuracy is also very precise at two to three millimeters from the source (Hämäläinen, Hari, Ilmoniemi, Knuutila, & Lounasmaa, 1993). The downside to this procedure is the cost and the bulkiness of the device. The strong magnetic field generated can also cause hassles with electronics and metallic objects. Similarly, the functional magnetic resonance imaging (fMRI) machines also analyze the magnetic fields generated by the electrical activity. The fMRI utilizes a large magnet in order to determine the source. It has very high spatial resolution as well as full brain coverage, but its temporal resolution is slow and the device is large and immobile (Ritter & Villringer, 2006). Out of the mentioned methods of brain wave monitoring, only the EEG is convenient for our needs. It has high temporal resolution for immediate analysis that is crucial when in a vehicle. Although it is simply not practical to monitor a driver’s brainwaves using a full EEG due to its complex setup of many electrodes, EEG headsets are a much cheaper, more convenient alternative. Since they have fewer electrodes, they are easier to use and more portable, but in exchange they are less accurate (Brown et al., 2010).

2.9 EEG Variation and Demographics

Brain waves vary significantly from person to person, from activity to activity, with different positions on the head and in complex interactions of these factors. Thus, EEG studies rarely find results that are absolute and generalized to the broader population.

Different psychiatric disorders typically lead to differences in important EEG values. With ADHD as one example, Clarke et al. (2002) find that children with ADHD have a higher theta to alpha power ratio when they are not being treated. This difference is more pronounced in the frontal lobe as measured by the electrodes near the front of the head. Chabot et al. (1999) were able to correctly predict, using only an EEG and with 85% accuracy, whether a stimulant medication would be effective.

Aging is also studied frequently. Several studies find statistically significant differences in brain waves across different age groups, but the effects are sometimes contradictory. For example, Kolev et al. (2002) find that there is a general decrease of alpha power with respect to other frequency bands. This change is most pronounced at the occipital locations but can also be found elsewhere. Duffy et al. (1984) corroborate this story by finding an increase in resting state beta wave activity in healthy older adults. Other studies find the contradictory result that there is a general shift in power towards the slower frequencies of delta, theta and alpha (Klass & Brenner, 1995). Further complicating the picture, Hartikainen et al. (1992) find that slow waves decrease in power as one ages, but increase in those who develop age related mental diseases. Some age related brain wave changes have been found and have not been contradicted by later studies. For example, Kikuchi finds a general decrease in interhemispheric coherence (i.e. the correlation in signal across hemispheres) across all frequency bands as age increases. The general effects of aging on brain waves are nevertheless inconclusive.

Another area frequently studied is sex differences in EEG signals. One of the more consistent sex difference findings is that men show more intrahemispheric correlation in alpha power, and women show more interhemispheric correlation in alpha power (Corsi-cabrera, Herrera & Malvido, 1989). High IQ men show greater alpha power in the right hemisphere than low IQ men when attempting spatial reasoning tasks (Ray et al., 1981), but women show no differences. Similarly, women of higher ability show higher alpha power when attempting verbal creativity tasks compared against low ability women, but men show no differences (Fink & Neubauer, 2006). Though these differences may seem random and improbable, the high (90%)

heritability of theta, alpha and beta frequencies suggest that EEGs are measuring very real, physical phenomena (van Beijsterveldt et al., 1996).

These important confounding factors make it difficult to easily detect drowsiness consistently. Hence, algorithm development is typically geared toward finding changes in important EEG values in the same person across time.

2.10 EEG Headsets

In our study, we used EEG headsets to measure brain waves. These are significantly different from the typical EEG in size, number of electrodes, complexity, resolution capabilities, and cost. One headset we used in our study is NeuroSky's Mindwave Mobile headset. This headset has a single dry electrode that is placed on the forehead above the left eyebrow and a reference and ground electrode on an ear clip (NeuroSky, 2015). The other EEG headset used in our study is the Emotiv Epoc, which has 2 references plus 14 wet electrodes which have to be moistened with saline (Emotiv, 2014). More on the differences between the two headsets will be discussed later.

2.11 Algorithms for Detecting Drowsiness

To detect brain waves with the few electrodes that can be used in a wearable device, algorithms have to be used to amplify the signal. Different mathematical, statistical, and algorithmic tools have been developed to analyze the raw EEG data. Drowsiness, more specifically, has been analyzed extensively due to the public safety and productivity concerns.

The criteria used to assess the validity of algorithms is the extent to which it normalizes for differences in EEG patterns between subjects, and the accuracy with which the algorithm predicts drowsy behavior in the subjects (Johnson et al., 2011). In the algorithmic analysis papers we studied, the accuracy of the algorithm being analyzed was measured in different ways. A common method is to have participants play a driving simulator which records the virtual vehicle's deviations from the center of the lane (Liang et al., 2005).

One algorithm to refine raw data is the EEG power spectral density (PSD) bandwidth comparisons. In this method, the EEG data is a set of random variables assumed to be a probability function. The signal is then amplified by filtering out the noise. Which packets in the data are the signals and which voltage spikes are just noise is estimated by repeated use of multiple devices that measure the alpha, theta and beta rhythms relevant for drowsiness testing (Oppenheim & Verghese, 2010). Liang et al. (2005) applied this more general method of amplifying and processing electromagnetic wave signals to EEG devices more specifically. They started with the standard 10-20 International Standard wet electrode placement, and narrowed the electrodes down to two using PSD. This was done by first amplifying the signals using all the electrodes and an EOG machine and then finding the two electrodes that gave the strongest correlation to driving performance. In other experiments, the researchers simply used linear regression to estimate correlation between full EEG data and driving patterns. A mathematical model takes EEG data input and reliably predicts the stability in driving as measured by deviations from the center of the lane (Chiou et al., 2006).

Finally, Fu et al. (2008), monitored drowsiness in subjects through principal component analysis (PCA). The algorithm, which employs similar mathematics to a linear regression model, takes a unit of time and models the corresponding EEG reading as a normally distributed random variable. The output of the model was calibrated to match closely with the driving performance of individuals.

The current literature in drowsiness detection algorithms has some glaring holes. First, most of the studies have very small sample sizes in the area of 30 participants (Robinson et al. 2011). In order to be able to use this algorithm on a wider population, more data points to calibrate the algorithm are necessary. The driving tasks that the noted studies used were all different, and there is not a standardized driving virtual simulator. Furthermore, there is not any mention of making useful comparisons between data from one virtual driving program to another virtual driving program. The computational power required also becomes a problem for some statistical tools like principal component analysis. A wireless, fully functional EEG headset will have to work with limited computational resources. Preferably, the chosen computationally inexpensive algorithm is also accurate.

Chapter 3: Overview of Devices

3.1 Device Comparison Criteria

In order to determine the “best” device for drowsy driving detection, we decided to compare several devices based on the following characteristics: price, convenience, and accuracy.

In recent years, various car companies have begun to include systems in their vehicles that can detect drowsy or distracted driving through a variety of methods. However these system are limited to specific car models. A lower-cost alternative for a drowsy driving detection system that does not rely on the car model would be much more accessible to potential consumers.

Our criteria of convenience includes ease of use, comfort, and practicality. A device that is difficult to use, causes discomfort, or limits the wearer in any way would discourage its use and potentially be a safety hazard. Therefore it must not only be user-friendly and comfortable to wear, but it also must not be obstructive to a driver’s range of motion or field of vision.

Most importantly, the device must be able to detect drowsiness both efficiently and accurately. The faster a device is able to detect drowsiness and with fewer false negatives, the safer it would be for the driver when combined with an alerting system.

3.2 NeuroSky Mindwave Mobile

Figure 3.2.1: NeuroSky Mindwave Mobile EEG headset.
Image retrieved from http://store.neurosky.com/

The NeuroSky Mindwave Mobile EEG headset was the first device our team looked into. It has a single dry electrode that is placed on the left forehead at the FP1 position as defined by the international 10-20 system of EEG electrode placement. It has a 512Hz sampling rate and a 3-100Hz frequency range (NeuroSky, 2015). It is powered by a single AAA battery. The NeuroSky Mindwave Mobile headset cost $130. The single dry electrode and grounding ear clip made this device easy to put on and position properly.

3.3 Emotiv EPOC

Figure 3.3.1: Emotiv EPOC EEG headset.
Image retrieved from http://emotiv.com/

The Emotiv EPOC headset was the second EEG headset our team looked into. It has 14 wet electrodes placed on the AF3, AF4, F3, F4, FC5, FC6, F7, F8, T7, T8, P7, P8, O1, and O2 positions and 2 reference electrodes on P3 and P4 as defined by the international 10-20 system. It has a sampling rate of 128 per sec and frequency response of 0.16 - 43 Hz (Emotiv, 2014). The Emotiv EPOC headset cost $700. The device had to be charged and the electrode pads had to be moistened with a saline solution prior to use. For proper storage, the pads and sensors are kept separate from the rest of the headset, so they had to be individually secured into place before use. The plastic arms connecting each electrode were slightly flexible, and thus had to be individually adjusted to ensure proper positioning.

3.4 MPU6050 Gyroscope

Figure 3.4.1: MPU 6050 Gyroscope.
Image retrieved from http://www.digibay.in/

The MPU6050 is a gyroscope and accelerometer combination that has ±250, ±500, ±1000, and ±2000°/sec or ±4.36, ±8.73, ±17.45, and ±34.91 rad/s settings for the gyroscope and ±2g, ±4g, ±8g and ±16g settings for the accelerometer. It is easily accessible and is easily used through an I2C open library. The MPU6050 gyroscope cost $10. A casing was 3D printed to mount the gyroscope on a pair of wearable glasses so we could track the user's head movements.

3.5 Modified Microsoft LifeCam HD-6000

Figure 3.5.1: Microsoft LifeCam HD-6000.
Image retrieved from http://www.amazon.com/

The camera we used was a Microsoft LifeCam HD-6000 Webcam for Notebooks, modified following the instructions of Brandyn White from WearScript (2014). It has 1280 X 720 pixel resolution and an imaging rate of up to 30 frames per second. The overall cost for the eye-tracking camera was around $40. After modification, a case was 3D printed to hold the camera in the correct position in relation to the subject's eye. However, we were unable to position the camera in a way that allowed for accurate eye tracking without obstructing a significant portion of the wearer's field of vision in one eye.

Chapter 4: Methods and Results - NeuroSky

4.1 Methodology

For dual goals of increasing the convenience and accuracy of drowsiness detection, we decided to first experiment with the NeuroSky headset. This EEG headset contains just one electrode positioned where the FP1 electrode would be placed by the 10-20 EEG placement system. While this position offers an advantage in being able to detect eye-blinks along with changes in wave powers, it was unknown whether this electrode placement was the optimal location for our algorithm. We chose the NeuroSky headset as it offered an API that allowed easy access to the raw data, and automatic calculation of Fast Fourier Transforms (FFT). The sampling rate was 512 Hz for raw data and 1 Hz for FFT power data.

4.1.1 Data Collection

Samples of raw data (evoked potentials) were gathered from three of the members of the team. Each person contributed roughly thirty minutes of data gathered at different times and split into awake and drowsy states. For the safety of our test subjects, none of the samples were collected while driving. Nevertheless, an effort was made to simulate the mental alertness states and driving conditions. Subjects were either playing games or doing math exercises in the morning or afternoon to simulate the awake state. For the drowsy state, each subject started gathering data late at night when he or she reported subjective drowsiness. One subject (ID: DD) gathered ten five minute samples each of drowsy and alert data. The other two subjects (ID: PH and EC) gathered three, five minute samples for each of drowsy and alert states. Two thirds of each subject's total collection was used as in-sample data for parameter estimation. The remaining one third of data was used as the out-sample data to determine prediction accuracy rates.

4.1.2 Drowsiness Detection – Histogram Method

For the first attempt at a drowsiness detection algorithm, we partitioned the signal into epochs of 64 points or segments of length 64 points each. We applied an FFT on this data-set to take it into the frequency domain. We then generated a histogram by binning the alpha power (8 - 12 Hz) results from 180 seconds of FFT output into 150 equally spaced bins across the spectrum of outputs. This produces a mapping between the center of each bin's range and the frequency or number of times the FFT value is in the corresponding alpha wave power range. Then, an exponential model of the form ae^{bx} is fit to the bin vs. frequency values using MATLAB's curve fit algorithm. Finally, we determine that the user is drowsy if the estimate for parameter b differs statistically significantly from the non-drowsy training data.

We decided to not use this algorithm because of how long it takes to work in real-time and how computationally expensive it is. The algorithm requires that the last 180 seconds of FFT output be continually histogrammed. This, along with the constant curve fitting to see if the current parameter value falls outside the confidence interval for the alert state consumes a great deal of resources. While the other detection method (described below) requires more training time, it's able to give diagnoses sooner in real time and with greater accuracy.

4.1.3 Drowsiness Detection – Probit Model

The second algorithm developed to distinguish drowsiness from alertness involves a Probit model. First, the raw evoked potentials from the NeuroSky headset was filtered through a high-pass filter with a minimum frequency of 1 Hz. Second, the signal was split into epochs of length 512. This resulting time domain signal was transformed into the frequency domain by applying an FFT. Once again, we select the EEG band of interest, alpha waves, and compute the absolute value of the frequency domain signal and sum the values across the band to get the total alpha power.

A proper Discrete Fourier Transform (DFT) requires a stationary time series, and the underlying phenomenon to be linear. Our data does not satisfy these assumptions. This isn't a problem insofar as we are attempting to merely create an algorithm that distinguished between the drowsy and alert states of a driver's EEG signal. Success in this goal isn't diminished by failing to uphold theoretical assumptions.

Hence, once the FFT is applied to the signal, we moved the frequency domain data to a Probit model where we regressed the binary response variable "drowsy" for each second on the corresponding alpha band power. Our model is defined:

$$P(drowsy_i = 1 \mid alpha_i) = \Phi(\alpha_i + \beta alpha_i)$$

We aim to estimate β. Along with the usual Gauss-Markov Theorem assumptions, we also assume that there is a latent variable, $drowsy_i *$, which determines the following: $drowsy_i = 1\, if\; drowsy_i * > 0\, and\; drowsy_i = 0\, otherwise$. This problem can then be reduced to an ordinary linear regression (Wooldridge, 2010).

The Probit model's parameters are estimated on in-sample data which have the data-points already classified between the drowsy and alert states for approximately twenty minutes of training data per subject. Finally, these estimated parameters are then used to predict out of sample data points and give a probability estimate for whether the subject is drowsy. This probability estimate can be reported as either a one or zero by applying a threshold rule to the estimate. For example, estimates for probability of being in the drowsy state above the threshold of 0.5 can be reported as one and zero otherwise. We used 0.3, 0.4, and 0.5 as thresholds and report these results in figures 4.2.1, 4.2.2 and 4.2.3 respectively.

4.2 Results

We find an overall accuracy rate for this method ranging from 58% to 76% accurately diagnosed (figure 4.2.2). The specific accuracy rates of interest are the true positive rate and the false negative rate. The true positive rate is the number of times the method accurately gave a drowsy diagnosis divided by the number of times the method gave a drowsy diagnosis. In other words, this number represents the confidence that a subject may have that he or she is truly drowsy when given a drowsy diagnosis. Again the results using this electrode placement and this sampling rate are highly variable ranging from 49% to 93% accuracy.

The next accuracy measure of interest is the false negative rate. We define a positive signal as a drowsy diagnosis, and a negative signal as its opposite. Hence, the false negative rate is defined as the number of times the method reports that the user is alert when in fact she is drowsy divided by the number of times the method reports an alert diagnosis. It's important to minimize the false negative rate to maximize the safety of the user. Our results vary from a high of 41% to a low of 14%.

The false negative rate depends crucially on the threshold value used to give a drowsy a diagnosis. A higher threshold makes it more difficult to acquire a drowsy signal and a lower threshold does the opposite. Hence, the false negative rate has a positive relationship with the threshold. Figures 4.2.1, 4.2.2 and 4.2.3 have the results with thresholds of 0.3, 0.4 and 0.5 respectively. The costs associated with decreasing the threshold value are an increase in the false positive rate and a decrease in the overall accuracy.

Subject ID	Channel	True Positive	True Negative	False Positive	False Negative	Percent Correct	Threshold
EC	FP1	73%	30%	49%	47%	51%	0.3
PH	FP1	96%	35%	39%	10%	67%	0.3
DD	FP1	50%	97%	6%	32%	74%	0.3

Figure 4.2.1: Neurosky reliability: 0.3 threshold

Subject ID	Channel	True Positive	True Negative	False Positive	False Negative	Percent Correct	Threshold
EC	FP1	63%	53%	43%	41%	58%	0.4
PH	FP1	93%	50%	34%	14%	72%	0.4
DD	FP1	49%	100%	0%	32%	76%	0.4

Figure 4.2.2: Neurosky reliability: 0.4 threshold

Subject ID	Channel	True Posi	True Negat	False Posi	False Nega	Percent Correct	Threshold
EC	FP1	53%	70%	36%	40%	62%	0.5
PH	FP1	86%	68%	26%	18%	77%	0.5
DD	FP1	45%	100%	0%	34%	74%	0.5

Figure 4.2.3: Neurosky reliability: 0.5 threshold

The average accuracy rate across all the subjects comes to 71%. While this isn't necessarily an unsatisfactory result, the corresponding false negative rates do make this an unsatisfactory result. We would want to alert a driver who is drifting into drowsiness more than we'd like to accurately determine that he is alert. For some subjects in some threshold levels, we fail to detect drowsiness 40% of the time. We find that the false negative rates are much too high to be able to be used in real-time, so we explored other electrode placements to augment or replace the FP1 placement.

Chapter 5: Methods and Results - Emotiv

5.1 Methodology

The Emotiv EPOC is a portable EEG headset which contains fourteen separate EEG channels at various points on the head (see section 3.2 for details). There were several goals in using the Emotiv headset. First, we wanted to determine if the FP1 electrode placement of the NeuroSky headset produces the strongest signal for detecting drowsiness or if there are more suitable channels. Second, we wished to find the costs and benefits to accuracy in using more than one channel at a time. Third, we wanted to measure the loss in accuracy that occurs in losing temporal resolution as the Emotiv has a sampling rate of 128 Hz for each channel compared to NeuroSky's 512 Hz.

5.1.1 Data Collection

Since we were interested in showing the different tools that can potentially be brought to detect drowsiness and the relative trade-offs, we did not acquire outside test subjects and large samples. The data used to show the effectiveness of the different EEG methods were collected from three umdRoute team members. We collected samples in a similar fashion to the way data was collected with NeuroSky (Section 4.1).

Each subject recorded his or her evoked potentials using the Emotiv headset while either doing puzzles or while drowsy but sitting still. Subject DD collected six minutes of in-sample drowsy data, six minutes of out-of-sample drowsy data, six minutes of in-sample alert data and six minutes of out-of-sample alert data. For each level of alertness, subject EC collected nine minutes of in-sample data and three minutes of out-of-sample data. Finally subject PH collected five minutes of data for each state. Since there was no separate out-of-sample data for PH, a portion of each five minute sample was excised and used to estimate parameters.

The EEG signal was processed in exactly the same way as in section 4.1, and the alpha power signal from each channel was used in the Probit model described in section 4.1.

5.2 Results

We adjusted several different variables and observed how the change affects the different measures of accuracy. The first objective was to determine if the placement of electrodes significantly changes the accuracy of the device. While using all 14 of the wet sensor electrodes of the Emotiv is surely too cumbersome when driving, we attempted to see if any smaller subset of electrodes was able to produce a signal useful to our method.

Using just one channel, we were able to find some high accuracy rates and some low ones. Since the sample for subject PH was very small, we were unable to get consistent or useful results. Nevertheless, that informs us that just five minutes of training data is insufficient to produce an accurate signal. The accuracy rates for subjects EC and DD are represented in figure 5.2.1.

Channel	DD Overall Accuracy	EC Overall Accuracy
AF3	81%	62%
F7	54%	74%
F3	56%	70%
FC5	09%	54%
T7	37%	65%
P7	62%	60%
O1	58%	70%
O2	37%	69%
P8	64%	74%
T8	26%	90%
FC6	58%	51%
F4	34%	59%
F8	56%	45%
AF4	44%	64%

Figure 5.2.1: Emotive accuracy by subject

The top performing electrode for each subject differed substantially. Indeed, the correlation of overall accuracy rate of each electrode between EC and DD was -0.08. The top performing electrodes for DD were AF3, P8 and P7 with accuracy rates of 81%, 64% and 63% respectively. For EC they were T8, P8 and F7 with 90%, 74%, and 74% respectively. The only overlap here is in channel P8. Nevertheless, with so much variance between the subjects, it’s too difficult to predict which position on the head yields a superior result.

The second variable of interest was the epoch length. An epoch is the length of time of sampling that goes into producing one alpha wave power data-point. Since the Emotiv has a sampling rate of 128 Hz, an epoch length of 1 second implies that we applied an FFT on every

128 data points of evoked potentials. We tried epochs of length 1 second and 2 seconds. The results of this change are depicted below.

When comparing the results from 1 second epoch to 2 second epoch, we find that there isn't much variance. The benefit to the quality of the FFT calculation seems to be counterbalanced by the fact that fewer calculations are produced.

Channel	**DD Overall Accuracy**	**EC Overall Accuracy**
AF3	81%	62%
F7	54%	74%
F3	56%	70%
FC5	9%	54%
T7	37%	65%
P7	62%	60%
O1	58%	70%
O2	37%	69%
P8	64%	74%
T8	26%	90%
FC6	58%	51%
F4	34%	59%
F8	56%	45%
AF4	44%	64%

Figure 5.2.2: Overall accuracy of predicting drowsy and non-drowsy states using a single channel with epochs of 2 seconds

The third possibility we explored was that some pairs of channels may be relatively uncorrelated with each other and produce a high accuracy. We chose to limit ourselves to looking at pairs of electrodes closely. This is because anything more than two electrodes would become too cumbersome to use in a real-world application, and the combinations of electrodes become fairly large when observing any set of three. We depict the top performing pairs of electrodes below.

Highest Accuracy Channel Pairs - DD

Subject	Channel Pair	False Negative	Overall Accuracy
DD	AF3 F3	15%	85%
DD	AF3 FC6	20%	84%
DD	AF3 P8	11%	82%
DD	AF3 O1	16%	81%
DD	AF3 P7	21%	75%

Figure 5.2.3: The top five electrode pairs by overall accuracy for DD

Highest Accuracy Channel Pairs - EC

Subject	Channel Pair	False Negative	Overall Accuracy
EC	O2 T8	11%	92%
EC	T8 AF4	11%	92%
EC	P8 T8	14%	92%
EC	AF3 T8	14%	91%
EC	O1 T8	16%	90%

Figure 5.2.4: The top five electrode pairs by overall accuracy for EC

It's apparent that the top performing electrode pair varies substantially between test subjects, and the top performing single electrode is always present in the top pair. It is also apparent that overall accuracy rates increase from the single channel. For DD the top performing single channel AF3 produced an accuracy rate of 81%, and that improves to 85% accuracy with the addition of one electrode. Similarly, for EC the top performing channel T8 yielded 90% accuracy and improved to 92% accuracy in combination with channel O2.

The fact that even the pairs don't correlate well between subjects implies that any device that attempts to fix the electrode in one location is likely to work well for some drivers and not for others. We do observe that the largest accuracies are obtained with greater training data. The sample for EC contains 50% more training data and it provides 20% greater accuracy in predictions across most channels.

The false negative rate also shows a substantial improvement over the NeuroSky single channel headset. Here, the false negative rates are at 11% for EC and DD in the highest functioning pairs compared to 40% with NeuroSky. This significant improvement allows this method to be usable. However, there is no way to determine which electrode is ideal for which person. Future researchers may explore the possibility of using a pair of adjustable electrodes to gain a more accurate reading.

We limit ourselves to two electrodes because the use of more than two does not always confer an advantage. To show this, we ranked the channels by overall accuracy rate for each subject. We tried to use the top channels in combination to predict the drowsiness of the subject. Doing this yields some moderate improvement for EC and no improvement at all for DD. This is not inconsistent with the findings above. The increase in accuracy from using two channels comes only when we know which two electrodes work well in tandem. If we were to simply select the top two electrodes by their solo performance, we gain no noticeable benefit.

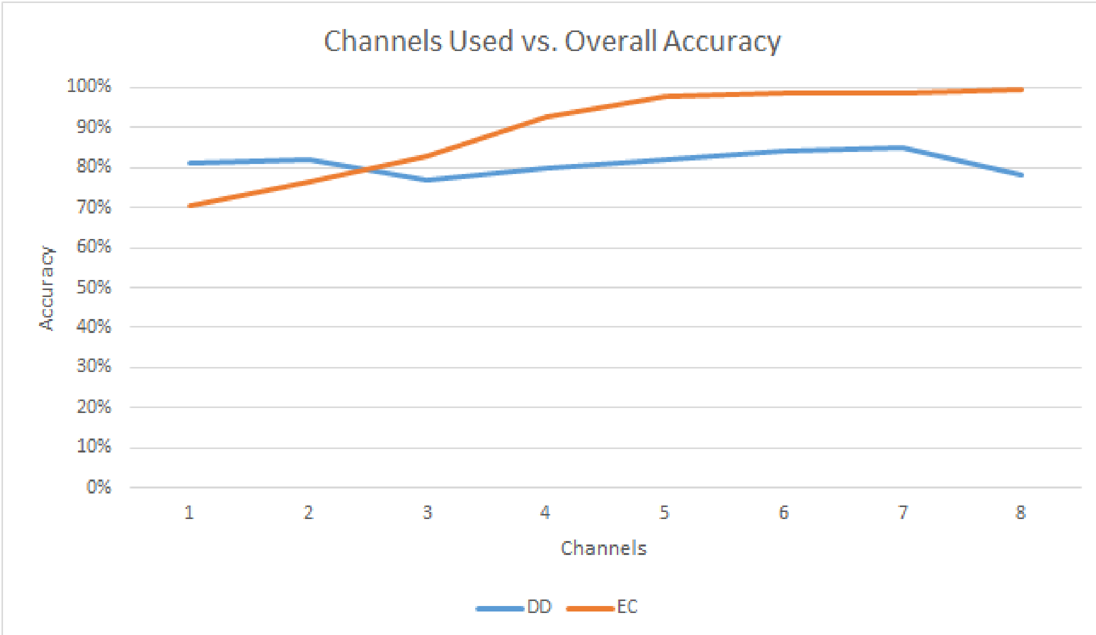

Figure 5.2.5: Accuracy of Emotiv with increase in channel count

Channels Used and Performance

Number of Channels	**True Positive**	**True Negative**	**False Positive**	**False Negative**	**Overall Accuracy**
			DD		
1	59%	97%	7%	24%	81%
2	86%	79%	25%	11%	82%
3	76%	77%	29%	18%	77%
4	76%	83%	24%	17%	80%
5	79%	84%	22%	15%	82%
6	76%	90%	15%	16%	84%
7	79%	88%	17%	15%	85%
8	69%	85%	24%	21%	78%
			EC		
1	83%	97%	3%	15%	90%
2	84%	99%	1%	14%	92%
3	80%	99%	1%	17%	90%
4	82%	98%	3%	16%	90%
5	89%	98%	2%	10%	94%
6	89%	98%	3%	11%	93%
7	86%	98%	2%	13%	92%
8	91%	96%	4%	9%	94%

Figure 5.2.6: Accuracy rates by number of channels used

Chapter 6: Methods and Results - Gyroscope

6.1 Methodology

With the gyroscope, we aimed to find a cheap and simplistic way to detect episodes of microsleep through the analysis of the user's head motions. The first step was to identify the problems and specify what methods and devices would best suit our needs for data collection through a gyroscope. At this we stage we identified that our main goals were to find characteristic head motions of a drowsy person and choose a device that can match our needs.

According to a 2005 study, the maximum angular rate for head motion is 9.03 rad/s and the maximum linear acceleration is 93.6 m/s^2 or 9.55g (Bussone, 2005). After researching potential gyroscopes, we found that most consumer gyroscopes can easily accommodate the 9.03 rad/s, but the 9.55g was slightly more difficult to find. In the end, we decided on the MPU6050 which has ±250, ±500, ±1000, and ±2000°/sec or ±4.36, ±8.73, ±17.45, and ±34.91 rad/s settings for the gyroscope and ±2g, ±4g, ±8g and ±16g settings for the accelerometer. We decided to utilize the 500°/sec and 8g settings since we were not looking for maximum movement, but rather a motion pattern defined while driving. By using a lower setting, the error margin for the device is lowered to give us a higher precision. In addition to matching our data collection requirements, the MPU6050 also has some features that reduced our need to filter out unnecessary data and is commonly used within the hobby electronics community and has an open source library by Jeff Rowberg that takes in the raw data and transforms it into human readable information. In order to fully utilize the MPU6050, we interfaced it with the Arduino

Uno and used Jeff Rowberg's I2C library from I2Cdevlib. The library allows us to directly collect the angle relative to the initial startup after a brief warming period.

Once we decided upon the device to be used, we required a method to attach the device to the user. When attaching the gyroscope to the user, we had to consider multiple factors including intrusiveness and comfort. Intrusiveness was defined as the amount that the device impairs the user and comfort was defined as how the device felt to wear. In this process we deliberated between attaching the device on a hat, headband, or a pair of glasses. With respect to the hat and headband, the gyroscope would constantly move as the user rotated which caused the data to have a higher margin of error and to be inconsistent. This lead to mounting the gyroscope onto a pair of glasses through a 3D printed attachment. This schematic was also used for the camera which is covered below.

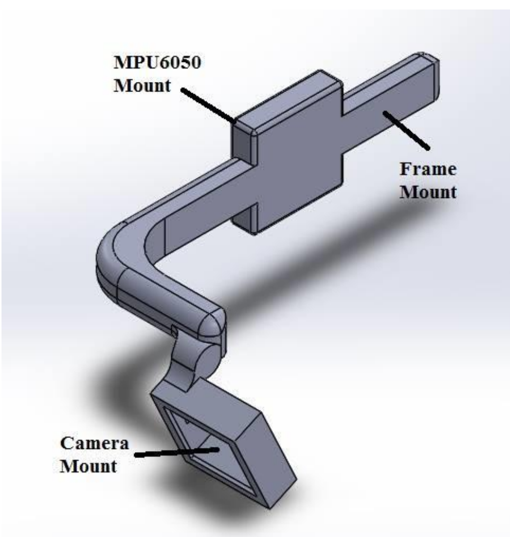

Figure 6.1.1: Gyroscope attachment

Figure 6.1.2: MPU 6050 Gyroscope. Image retrieved from http://www.digibay.in

The next step was to decide upon methods to measure drowsiness. The first method to measure drowsiness was through the presence, duration, and occurrence of head nods. While head-nods are considered to occur after alertness has already dropped, we decided that it could be used as a final fail-safe in case of other detection failures (Haworth & Vulcan, 1991). For our head-nod algorithm, we used a two criteria process. The first criterion was through measuring the duration in which the user's head was angled below a certain threshold. For our experiment we chose a minimum duration of 1 seconds when the user's head falls below 8° to denote that the user has nodded off. The duration of 1 seconds was chosen liberally to ensure that the user has actually nodded off and not be doing routine driving tasks such as changing gears or adjusting settings on his dashboard. The second criteria used was made by checking for a priming motion which was defined by a falling acceleration motion for the head. For our experiment we utilized a minimum angular velocity of 20°/s and a minimum angular acceleration of $200°/s^2$. We then counted the number of head nods given in each state and averaged them by the amount of time of the samples to get a resultant frequency of head-nods.

The second analysis was of the deviations in position and angular velocity. Despite head motions being a possible indicator of fatigue or drowsiness, there have been few studies indicating the differences between the patterns observed during sleep-deprived and non sleep-deprived states (Van den Berg, 2006). The first analysis of angular velocity is done by congregating all of the data and creating a histogram through MATLAB and find the curve of best fit. The second analysis is of the angular position of the user's head through calculating standard deviations. Once we find the standard deviations we will compare them with the additional standard deviations given by additional data.

Since we were testing the plausibility of the different methods of analysis we took multiple samples from one member of our team. The goal of using one user is to see if it is possible to personalize the gyroscope for a particular user. To control the data, we made the subject sleep for 8 hours prior to collecting data at sometime in the afternoon from 12PM to 6PM for concentrated data and from 10PM to 6AM for drowsy data. The time frames were chosen according to a study on the effects of the time-of-day and drowsiness in drivers (Wylie et al., 1996). The user is told to read from a screen placed directly perpendicular to his line of sight such that they naturally face forward. For the initial analysis each sample is of 20 minutes and five samples were taken. These were used for the calculations of the number of head nods, standard deviations and histogram analysis.

6.2 Results

6.2.1 Head Nods

When we measured for the amount of head nods, we split the analysis into two different portions. The first portion determined head nods by the amount of time that the user's head was below a certain threshold. In this case, we found it consistent with prior research conducted since the measured head nods increased during the drowsy state (Roge, Pebayle, & Muzet, 2001).

State	Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Average
Awake	0.1	0.05	0.15	0	0.1	0.08
Drowsy	0.45	0.1	0.15	0.75	0.7	0.43

Figure 6.2.1.1: Frequency of head nods based on duration of time over threshold in nods/minute

From our measurements, the user would be around 5 times as likely to drop their head for the longer duration during a non-alert state. According to Roge et al., the user should adjust their posture, which includes head nods, 1.5 times more likely during a drowsy state (Roge et al., 2001). Since our measurement for our user indicates a significantly higher likelihood for head nods, there is a high chance that we could use head nods to detect drowsiness. However, there is a high probability of finding false positives and false negatives since the deviation from sample to sample varied greatly. Samples 2 and 3 for drowsy is far closer to the awake state rather than the drowsy state which indicates that they are false negatives and would cause potential danger to the driver by failing to alert the user of their drowsiness. With a small sample size it is difficult to have a definite conclusion; however, our data indicates that there would be a 40% false negative rate. A possible reason for the discrepancies in readings is that the user indicated that he was far drowsier during the fourth and fifth samples and was still relatively awake during the second and third readings.

State	Type	Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Total
Awake	Average	1.95	3.85	7.22	0	2.3	4.25
	Standard Deviation	0.94	0	2.37	0	0.71	2.83
Drowsy	Average	2.9	2.32	5.49	6.68	6.56	5.56
	Standard Deviation	2.23	0.17	3.44	7.44	7.71	6.58

Figure 6.2.1.2: Average and standard deviation of duration of head nods based on duration of time over threshold in seconds

The data for the average duration of the nods seem to be a better indicator for drowsiness. Since the third awake sample has a significantly higher average duration, it is extremely likely that it was an outlier and should be ignored in our calculations. Once we ignore the third sample the average comes out to be 2.47 seconds per nod with a standard deviation of 1.02 seconds. Our data indicates that there is a 20% chance for false positives and a 40% chance for false negatives. Similar to the frequency, our findings follow what prior studies have shown (Roge et al., 2001).

State	Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Average	Standard Deviation
Awake	0.85	0.9	0.35	0.6	0.45	0.63	0.21
Drowsy	1.6	1.2	0.65	1.65	0.8	1.18	0.4

Figure 6.2.1.3: Frequency of head nods based upon a priming motion in nods/minute

Figure 6.2.1.3 shows a strong correlation between drowsiness and the amount of head nods based upon the priming motion. However, there is still a 40% false positive rate and a 40% false negative rate. We believe that a more thorough pattern could narrow these rates down since we took a liberal approach to how a head nod behaves.

6.2.2 Angular Position and Angular Velocity

From Figure 6.2.2.2 below, it can be noted that the user's head position deviates more often when the user is drowsy. This information is verified upon closer look in Figure 6.2.2.1 of the standard deviations of the user's head position. The standard deviation of the pitch is almost aways higher during the drowsy state except for the second drowsy sample. However, the standard deviation of the roll only deviates slightly for most cases. This can be attributed to roll being the side to side motion of the head and pitch being the up and down motion of the head. Combining both pitch and roll of the head, we get one false positive and no false negatives.

State	**Sample 1**		**Sample 2**		**Sample 3**		**Sample 4**		**Sample 5**		**Average**	
	roll	*pitch*	*roll*	*pitch*	*roll*	*pitch*	*roll*	*pitch*	*roll*	*pitch*	*roll*	*pitch*
Awake	3.26	3.08	3.43	3.59	2.61	3.96	3.28	3.07	2.48	3.12	3.12	3.59
Drowsy	3.89	4.39	3.52	3.64	3.22	4.17	3.33	6.13	3	6.11	3.83	5.22

Figure 6.2.2.1: Standard deviation of position angles in degrees

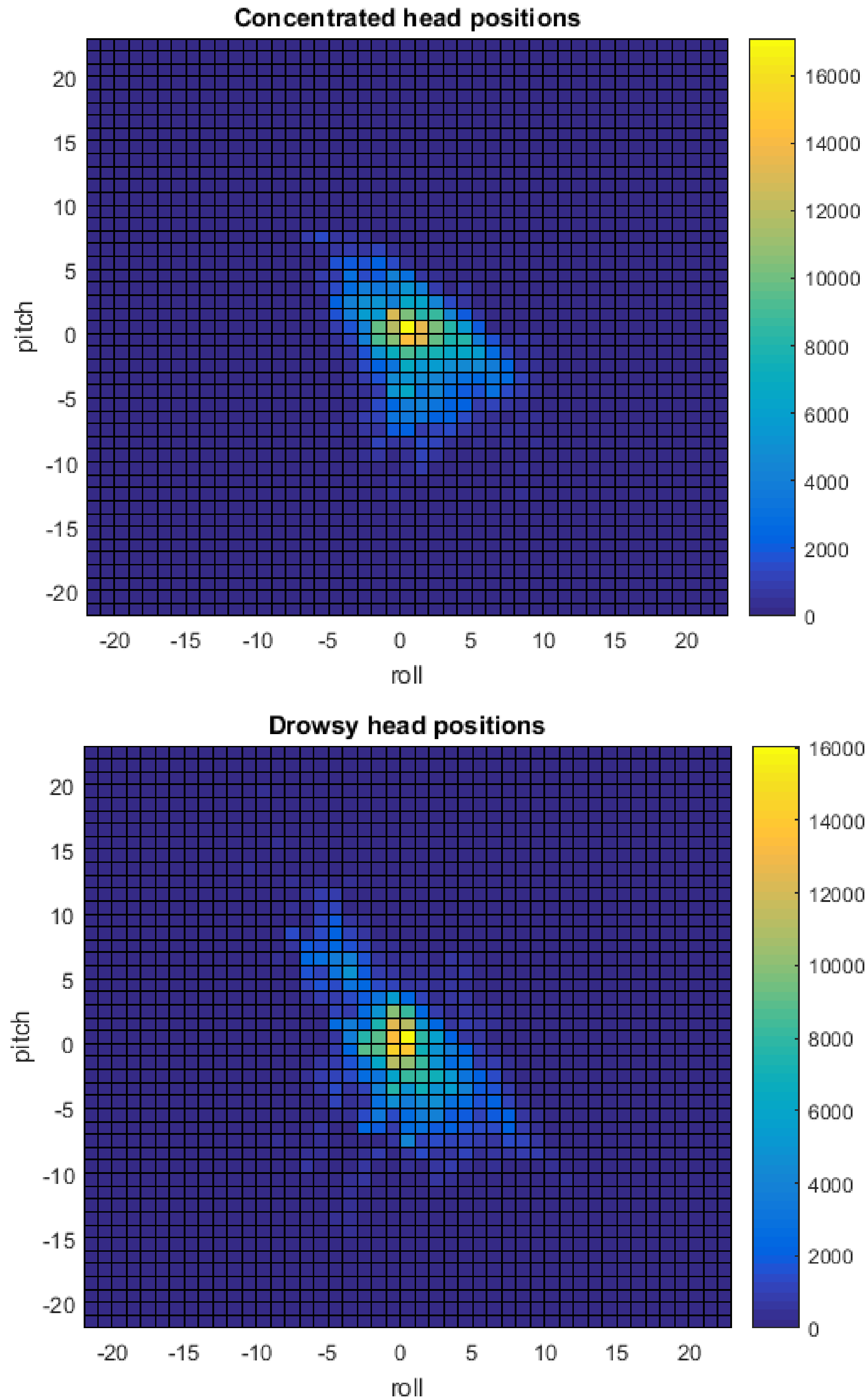

Figure 6.2.2.1: Head Position Distribution

Originally, we had hoped to find a significant difference between the angular velocity distributions; however, Figure 6.2.2.2 clearly shows that the difference is very slight.

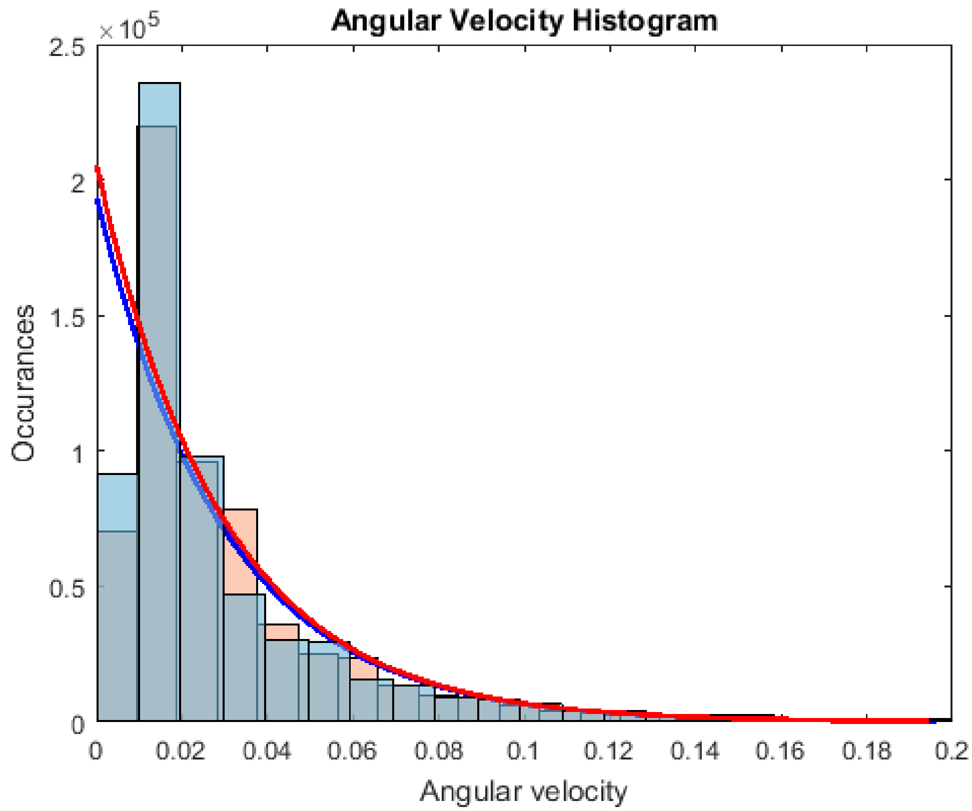

Figure 6.2.2.2: Angular Velocity Histogram

Chapter 7: Methods and Results - Camera

7.1 Methodology

The camera was originally to be used in conjunction with the gyroscope to measure the user's vestibulo-occular reflex or VOR. The VOR is essentially the eye's rotation to stay focused upon a target during the movement of the user's head. The first step to tracking VOR was to obtain a method of eye tracking. Our first eye tracking algorithm was WearScript which is an open source eye-tracking software. To implement WearScript we required a modified camera that could detect infrared light. The device we chose was the Microsoft LifeCam HD 6000 with modifications that were specified under WearScript's website. To enable the IR capabilities of the camera, we first disassembled the camera before removing the IR filter located on the lens. After we removed the default LEDs and replaced them with infrared ones. However, once we began interfacing with the camera, WearScript changed how they supported the camera to utilized google glass. At this point we switched over to the very similar Pupil to track the eye movements. Once we began testing the camera, we soon realized that it would be difficult to track VOR given how much the video feed stuttered once it ran through Pupil. The original plan to use VOR was to calculate the rotation of the eye based upon the captured movement before comparing that with the head motion data received from the MPU6050 gyroscope and accelerometer. The module that we used to attach the camera to the user is described in Figure 6.1.1.

7.2 Results

When we began, we collected data through the camera by mapping the pupil location into a comma separated values or .csv file. During this phase we ran into issues dealing with the device's internal timestamp and Linux timestamp. The desynchronization was simple to fix by creating a boot-up sequence that mapped the two times together. Soon after we ran into additional issues due to the software's poor frame rate. In the end we decided that it was best to discontinue research into VOR due to the prohibitive cost for a better camera.

Chapter 8: Comparison of All Results and Summary of Findings

8.1 Goal of Findings

In order to determine which device is most useful for alerting a driver, and to facilitate future work in alerting drowsy drivers, we prioritize the criteria in order of importance as follows:

Devices:

1. Ability to detect drowsiness
2. Portability
3. High level of accuracy
4. Minimal amounts of false negatives
5. Minimal amount of time to detect drowsiness

8.2 Summary of Results

	Cost	**Detection Time**	**Accuracy**	**False Positives vs False Negatives**	**Comfort (1-5 stars)**	**Portability (1-5 stars)**
NeuroSky	$130	10 minutes (training)	71%	18%/31%	4.2	3
Emotiv	$700	10 minutes (training)	85%	5%/15%	2.3	3
Gyroscope	$10	20 minutes warm-up	60%	40%/20%	4.5	4

Figure 8.2.1: Summary of Results

8.3 Trade-Off Analysis

The drawback of using multiple electrodes is in first determining the position of the extra electrode. This could take more than the minimal 10 minutes of training required to start using the device effectively. In addition, multiple electrodes are even less appealing than one electrode, and more cumbersome. Our electrodes had a slower sampling rate and they were wet. This makes a full comparison to NeuroSky's headset challenging. However, we can say definitively that wet electrodes are less convenient due to the need to keep them moisturized.

The camera and gyroscope did not have the detailed resolution we needed to do vestibulo-ocular reflex detection done by previous researchers, and head nods was insufficient for accurate drowsiness detection. The gyroscope could potentially be useful through the measurements of head position; however, more research is required to refine the technique. These were the cheapest devices. EEG was the most cost-effective technique that was successful at detecting drowsiness.

Chapter 9: Discussion and Future Work

9.1 Comparison of Drowsiness Detection Devices

Throughout the course of our research, we have discovered numerous drowsiness detection devices, all with their own advantages and disadvantages. Most of these devices have already been described in detail throughout the course of this paper, but will be recounted here along with our reasons for using them or discarding them in favor of another method.

One device we acknowledged, but did not seriously consider using, was a simple smart phone with an app which would prompt the user with questions and gauge their alertness based on the speed and accuracy with which they answered. This device would be impractical to use while driving, as it would require too much of the drivers attention and would distract from their real job of driving. However, we did consider using a simpler version of this system as a way of keeping the driver awake when they became drowsy, and used something similar in order to gain a measure of our own alertness while testing the reliability of our other devices.

The simplest device we have considered using is the gyroscope. Using this device, we would be able to determine how tired a person was based on the rate and amplitude with which they nodded their head. This approach to drowsiness detection was appealing, as the gyroscope chip was cheap and unobtrusive. This meant that the user would hardly notice it at all while driving, and thus would not distract or annoy them. At present, our gyroscope does not give us all of the accuracy we want, but has been shown to be capable of detecting drowsiness.

Moreover, we obtained a significant amount of data while learning this, and it helped us use it for other parts of our project.

Two of our proposed drowsiness detection plans revolved around the use of a camera monitoring the user's eye. This line of research was inspired by a program we found which utilized Google Glass and a retrofitted web cam to monitor a person's eye and intuit different commands. The web cam was much cheaper than the NeuroSky device, which was our main alternative at the time, and we were able to 3D print a cradle for it so that we did not have to buy a Google Glass in order to use it. In total, the apparatus cost around $20. The simpler of the designs we used just involved the camera, and involved monitoring a persons blink rate to find out how drowsy they were. Unfortunately, we ran into a similar problem to the one we had with the gyroscope, where detection would only occur when the user was nearing a point where their drowsiness could impair their driving ability. The other design we chose was more complicated, and for most of our time researching drowsiness detection, far more promising than all of the other devices we were considering. This design measured the vestibulo-ocular reflex, which had been previously shown to have a direct correlation to an individual's level of fatigue. The biggest obstacle to this design plan was the fact that it involved significant computational roadblocks. In order for this design to work, the camera had to be able to accurately track the persons retina which, while complicated, was fairly easy to set up. However, the device then had to coordinate the motions of the person's eye with the vibrations of their head, which involved syncing two asynchronous clocks from two separate devices. After attempting to do this, it was realized that the difference in the clocks added so much error to the final result that any data gained from the device was unreliable at best. Because of this, the device had to be abandoned.

One other major problem with both of these devices was that they obstructed the users view. While the camera could be moved so as to be less noticeable and obtrusive, it still remained as an obstacle that could annoy the driver. Since this defeated the purpose of the device, we had to move on to other designs.

The design we finally settled on was one we had planned on using from the beginning. We were already aware of an EEGs ability to detect peoples brainwaves, and thought it would be an obvious choice for a way to detect how tired a person was. To this end, we purchased a NeuroSky headset, in order to test the capabilities of the system. While we were at first disappointed with the accuracy of the device and the cumbersome feedback system, we eventually managed to get it to work reliably and with a satisfactory degree of accuracy. However, we found the false negative rate, the rate at which the device falsely implies that the driver is alert, was too high to use. Moreover, while the device isn’t necessarily comfortable, it is not so obnoxious that it would distract a person from driving safely. Because of this, we decided to use an EEG as our primary method of drowsiness detection.

9.2 Expected Use Cases

Although the present device is not yet useable in a real driving situation, we expect that a drowsiness detecting wearable device similar to our own has many practical use cases. Commercial drivers such as truck drivers or bus drivers are often required to drive long, monotonous routes late at night. In addition, the financial incentive for the individual truck driver is to maximize hours spent driving which may not be optimal for his employer or society. Thus, we expect that logistics companies would require drivers to use a drowsiness detection device, and insurers would give discounts for those who do. A similar argument can be made for people who operate dangerous machinery for work.

In general, since the device can be used in any situation where alertness is important, consumers might find uses outside of driving. For example, it may be useful to determine one's level of drowsiness before a high stakes exam. It may be useful to determine how many hours of sleep one needs to receive a minimal amount of "drowsy" classifications by the machine. In these other cases, the value can even be enhanced by future researchers or companies by developing algorithms optimized for that case.

9.3 Moving Forward with EEG Devices

At our present juncture, the best drowsiness detection device we have costs $700, not including the attachments necessary to help keep the driver alert. While this may not be cheap enough for the average driver, it does represent a significant step forward in combating drowsy driving. We expect costs to decrease if future devices contain two adjustable electrodes instead of 14 fixed electrodes. The first EEG device we purchased was the NeuroSky, which cost $130 and didn't give us the detail we needed to accurately predict drowsiness. The more detailed yet significantly slower Emotiv was significantly more expensive than that, but it was able to give us an idea of what channels and areas of the head provide the best indicators of drowsiness. Using this knowledge, we can take a simpler EEG device, as fast as the NeuroSky, and make it more accurate. Similarly, having used the NeuroSky and Emotiv devices to investigate how EEGs work, we can probably construct a cheaper, simpler device that could suit our purposes while remaining attractive to potential buyers. At its core, an EEG simply measures the voltage difference between two locations on the scalp, then amplifies the data it receives and finds the frequency associated with it. After doing this, the NeuroSky and Emotiv devices manipulate the data in order to make it more comprehensible and useful for the user. We can bypass this step of the process and send the EEG data directly to a processing unit which can determine from the simplified data whether or not the user is drowsy. Given the proliferation of smart phones and other such devices, the code necessary to determine drowsiness can, in most cases, be run from an app the user downloads themselves. This further decreases the cost by bypassing the need for a separate computer to interpret the EEG data. As has been established earlier, smart phone apps can also be used to establish the users alertness and prevent drowsiness. Given all of these considerations, we are certain we can design a reliable and comfortable drowsiness detection system which can be purchased at a price reasonable enough to make it available for the average consumer. This would be a two-electrode device. The placement of the electrodes could be optimized for each wearer. Through this device, we hope to make driving a safer experience by reducing accidents due to drowsy driving.

9.4 Moving Forward with Gyroscope

At this point, it has been shown that it is possible to detect drowsiness through the analysis of head motions. In future studies a more accurate gyroscope could be used since the MPU6050 seemed prone to have drifting data occasionally. The yaw axis for the gyroscope was not steady; thus, it was difficult to continue with it and the camera for VOR detection. In addition to a better device, new algorithms could be applied to determine patterns of tiredness such as feed drowsy data into a machine learning algorithm. As not all users wear glasses, a more sturdy or easily accessible method of attaching the gyroscope would be useful to research. Finally, signal isolation would be necessary to analyze head motion in a car. At a small cost of $10, the gyroscope could potentially add security to a drowsy driving detection system. The gyroscope may be combined with other detection to increase accuracy.

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