بسم الله الرحمن الرحيم

SLEEP ANALYSIS BY USING MINIMUM EEG LEAD SYSTEM

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Declaration of Authorship

This is to certify that the work presented here is the outcome of the study and analysis performed by Sifat Shahriar Khan, Ashfak Uddin Ahmed and Rashedul Hasan under the supervision of Md. Taslim Reza in the Department of Electrical and Electronic Engineering (EEE), Islamic University of Technology, Gazipur, Bangladesh. It is also declared that neither of the thesis nor any part of it, has been submitted anywhere else for any degree or diploma. Information derived from the published and unpublished work of others has been acknowledged in the text and a list of references is given.

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Abstract

Each and every day, thousands of people lose their lives in accidents occurring in roads and highways all over the world. Although there are many factors behind these collisions, one of the most significant reasons is drowsy driving. Drowsiness is a serious issue for the drivers since driving needs a sustained attention. So detection of drowsiness is necessary to prevent drowsy driving. By analyzing different bio-logical signals, we can point out drowsiness and fatigue level of a driver. Studies are going on to find systems capable of monitoring the biological condition of a driver and issuing warnings during the instance of drowsiness and inattention. Electroencephalogram (EEG) is the electrical activity of brain which is easily affected by fatigue and sleep deprivation. In this study, we are proposing a drowsiness detection system using frequency domain analysis and power spectral analysis of a single channel EEG signal. Here we propose an algorithm for differentiating between normal and sleepy condition. Thus drowsy driving and its subsequent catastrophe can be avoided by monitoring the brain activity of the driver and taking proper measures based upon the detection of drowsiness.

Chapter 1: Introduction

1.1 Drowsy Driving

Car accident occurs when a vehicle collides with another vehicle, pedestrian, animal, road debris, or other stationary obstruction, such as a tree or utility pole. Traffic collisions usually result in injury, death, vehicle damage, and property damage. Vehicle collisions lead to death and physical disability as well as financial costs to both society and the individuals involved.

Different factors contribute to the risk of collisions such as vehicle design, speed of operation, road design, road environment, driver skill or impairment, and driver behavior.

Many different terms are commonly used to describe vehicle collisions. The World Health Organization use the term road traffic injury,[1] while the U.S. Census Bureau uses the term motor vehicle accidents (MVA),[2] and Transport Canada uses the term "motor vehicle traffic collision" (MVTC).[3]

When a person does not get an adequate amount of sleep his or her ability to function is affected. As a result, their coordination is impaired, have longer reaction time, impairs judgment, and memory is impaired.

Sleep-deprived driving (commonly known as tired driving, drowsy driving, or fatigued driving) is the operation of a motor vehicle while being cognitively impaired by a lack of sleep. Sleep deprivation is a major cause of motor vehicle accidents, and it can impair the human brain as much as alcohol can.[4]

A very crucial factor contributing to road accidents is Sleep-Deprived Driving also known as Drowsy Driving. This sleep-deprived driving causes Micro-Sleep while driving.

It is no surprise then that the National Transportation Safety Board (NTSB) reported that drowsy driving was probably the cause of more than half of crashes leading to a truck driver's death. [93, 94] For each truck driver fatality, another three to four people are killed. [88]

Sleepiness can impair driving performance as much as or more so than alcohol, studies show. [14]

The consensus among drowsy driving experts is that in order to prevent many deadly crashes, it is critical to educate all people about the importance of adequate sleep and the dangers of not driving drowsy, with some experts calling drowsy driving a "silent killer" that needs a major public health and education campaign to counter. [8]

1.2 Drowsy Driving- its severity:

1.2.1 Statistics

A 1985 study by K. Rumar, using British and American crash reports as data, found that 57% of crashes were due solely to driver factors, 27% to combined roadway and driver factors, 6% to combined vehicle and driver factors, 3% solely to roadway factors, 3% to combined roadway, driver, and vehicle factors, 2% solely to vehicle factors, and 1% to combined roadway and vehicle factors.[5]

According to a 1998 survey, 23% of adults have fallen asleep while driving.[6] According to the United States Department of Transportation, male drivers admit to have fallen asleep while driving twice as much as female drivers.[7]

In the United States, 250,000 drivers fall asleep at the wheel every day, according to the Division of Sleep Medicine at Harvard Medical School and in a national poll by the National Sleep Foundation, 54% of adult drivers said they had driven while drowsy during the past year with 28% saying they had actually fallen asleep while driving. According to the National Highway Traffic Safety Administration, drowsy driving is a factor in more than 100,000 crashes, resulting in 1,550 deaths and 40,000 injuries annually in the USA.[8]

It has been estimated that between 16% and 60% of all accidents have sleep deprivation as a cause.[9] Between 1989 and 1993, it has been estimated that an average of 1,544 people were killed annually in the US as a result of sleep-deprived driving.[6]

The American Automobile Association (AAA) estimates that one out of every six (16.5%) deadly traffic accidents, and one out of eight (12.5%) crashes requiring hospitalization of car drivers or passengers is due to drowsy driving.[79]

One analysis estimated the cost of automobile accidents attributed to sleepiness to be between $29.2 billion and $37.9 billion. [82]

41% drivers admitted to having fallen asleep at the wheel at some point; one in ten drivers (10%) reporting they did so within the past year.[79]

More than one-quarter of drivers (27%) admitting they had driven while they were “so sleepy that [they] had a hard time keeping [their] eyes open” within the past month.[79]

In the National Sleep Foundation’s Sleep in America 2009 poll, more than half of adults (54%) reported they have driven at least once while drowsy in the past year, with almost a third (28%) reporting that they do so at least once per month.

1.2.2 Indication of Drowsiness

There are different signs which indicate the drowsiness of a driver. [84, 96]

- Difficulty focusing, frequent blinking, or heavy eyelids
- Daydreaming; wandering/disconnected thoughts
- Trouble remembering last few miles driven or missing exits and streets signs
- Yawning repeatedly/rubbing eyes
- Trouble keeping head up
- Drifting from lane to lane, tailgating, or hitting a shoulder or rumble strip
- Feeling restless and irritable[10]
- Ending up too close to cars in front.
- Missing road signs or drive past your turn.

Currently, there is no definitive physiologic test or detection system for drowsiness equivalent to the breath analyzers used to detect drunk driving.

Although people who fall asleep for more than a few minutes are often aware of those lapses in wakefulness, drivers may not be aware of shorter lapses and microsleeps, which can also have serious consequences when a quick reaction is needed to avoid high-speed crashes. [78]

1.2.3 Drivers at Risk

Drivers of different age and conditions are susceptible to drowsy driving.

- Young male drivers
- Shift workers and business travelers
- Drivers who regularly don't get enough sleep
- Drivers who have been awake for a long period of time
- Drivers who have untreated sleep disorders
- Drivers who use medications that make you drowsy
- Drivers who have been drinking alcohol

Commercial truck drivers are especially susceptible to drowsy driving. A recent study of 80 long-haul truck drivers in the United States and Canada found that drivers averaged less than 5 hours of sleep per day. For each truck driver fatality, another three to four people are killed.[11] In the fall of 2013 a new law was passed in the USA requiring the Federal Motor Carrier Safety Administration to propose guidelines related to screening for sleep apnea among commercial drivers.[12] The US military estimates that approximately 9% of crashes resulting in death or serious injury during Operation Desert Storm and Operation Desert Shield were caused by sleep-deprived driving.[6]

In one study, 82% of drowsy-driving crashes involved someone driving alone. A single driver has no one to talk to who can help keep him alert. Other people in a car will often notice when the driver is getting sleepy. Driving with others allows taking turns behind the wheel.

1.2.4 The problem occurs during late-night hours

Drowsy-driving crashes occur predominantly after midnight, with a smaller secondary peak in the mid-afternoon (Studies of police crash reports: Pack, Knipling, Wang, New York State GTSC Sleep Task Force, New York State Task Force on Drowsy Driving, Langlois, Lavie, Mitler, Horne, Reyner; Studies based on driver self-reports: Maycock, McCartt). [95][97-105] According to a 1996 report, time of day was the most consistent factor influencing driver fatigue and alertness. Driver drowsiness was markedly greater during night driving than during daytime driving, with drowsiness peaking from late evening until dawn. [106] Nighttime and mid-afternoon peaks are consistent with human circadian sleepiness patterns.

1.2.5 Government response to sleep-deprived driving

Governments had attempted to reduce sleep-deprived driving through education messages and by ingraining roads with dents, known as rumble strips in the US, which cause a noise when drivers wander out of their lane. The Government of Western Australia recently introduced a "Driver Reviver" program where drivers can receive free coffee to help them stay awake.[13]

1.2.6 Drowsy driving crashes result in high personal and economic costs

- Several drowsy driving incidents have resulted in jail sentences for the driver.
- Multi-million dollar settlements have been awarded to families of crash victims as a result of lawsuits filed against individuals as well as businesses whose employees were involved in drowsy driving crashes.

1.2.7 Drowsy Driving and Alcohol

Cognitive impairment after approximately 18 hours awake is similar to that of someone with a blood alcohol content (BAC) of 0.05%.[8-10] After about 24 hours awake, impairment is equivalent to a BAC of 0.10%, higher than the legal limit in all states.[14-15]

In addition, lower levels of alcohol (below the legal limit) amplify the effects of inadequate sleep. [16-17]

There are many commercially available devices to detect drunk driving, but no such device has been introduced commercially to detect and prevent drowsy driving.

1.3 Objective of the Study:

Drowsy driving is prevalent and major public health and safety concern. Considering the severity of drowsy driving, it deserves more attention. We dedicate our study to drowsy driving and how it can be detected before the occurrence of any collision. Research works are ongoing all over the world related to drowsy driving detection. Our aim is to contribute to this field by applying different methods through which we can determine drowsiness level and detect microsleeps.

We intend on using Electroencephalography (EEG) as our primary biological signal from which we want to detect drowsiness using different signal processing techniques.

1.4 Study Area:

In this study, we are going to focus on different signal processing and filtering techniques. In this study we want to come up with our own algorithm for sleep detection. The ins and outs of EEG and data acquisition procedures are one of the most important parts of our study. How many channels we need, and which channels we are going to use all of these are part of our study.

Noise Filtering, Artifact reduction are necessary for EEG signal processing. Hence we are also going to focus on noise and artifact filtering and compare between different techniques.

Finally the most important part of this study is signal processing using which efficient and effective detection of drowsiness with minimum possible delay is possible. There are different methods of analysis such as Time-domain Analysis, Frequency Domain Analysis and Pattern related analysis. There is also entropy based analysis methods.

In this study we mainly focus on frequency domain analysis such as Fast Fourier transform, power spectral density analysis, Gabor transform and Wavelet transform. Time Domain analysis such as correlation, mean and variance is also required in this study.

1.5 Limitations

Since this study is both simulation and experiment based, the main limitation is combining the results of simulation and experimental implementation.

Another limitation is noise and artifacts in EEG signal. We tried our best in this study to combine different filters and tackle this problem.

Usually drivers do not like wearing any sort of gear while driving since it is uncomfortable for the driver. In order to acquire EEG signal, electrodes are required. Using these sensors wirelessly or through the seat of the driver is possible but it’s difficult to implement and requires more advanced research.

Chapter 2: Literature Review

2.1 Sleep

Sleep is a naturally recurring state characterized by altered consciousness, relatively inhibited sensory activity, and inhibition of nearly all voluntary muscles.[18] It is distinguished from wakefulness by a decreased ability to react to stimuli, and it is more easily reversible than being in hibernation or a coma.

During sleep, most systems are in a heightened anabolic state, accentuating the growth and rejuvenation of the immune, nervous, skeletal, and muscular systems.

The purposes and mechanisms of sleep are only partially clear and the subject of substantial ongoing research.[19]

2.1.1 Stages of Sleep

Sleep is divided into two broad types: rapid eye movement (REM sleep) and non-rapid eye movement (NREM or non-REM sleep). Each type has a distinct set of physiological and neurological features associated with it. REM sleep is associated with the capability of dreaming.[20] The American Academy of Sleep Medicine (AASM) divides NREM into three stages: N1, N2, and N3, the last of which is also called delta sleep or slow-wave sleep.[21]

Stages:

- NREM stage 1: This is a stage between sleep and wakefulness. The muscles are active, and the eyes roll slowly, opening and closing moderately.

- NREM stage 2: In this stage, theta activity is observed and sleepers become gradually harder to awaken; the alpha waves of the previous stage are interrupted by abrupt activity called sleep spindles and K-complexes.[22]

- NREM stage 3: Formerly divided into stages 3 and 4, this stage is called slow-wave sleep (SWS). Slow wave sleep initiates in the preoptic area and consists of delta activity, high amplitude waves at less than 3.5 Hz. The sleeper is less responsive to the environment; many environmental stimuli no longer produce any reactions.

- REM: The sleeper now enters rapid eye movement (REM) where most muscles are paralyzed. REM sleep is turned on by acetylcholine secretion and is inhibited by neurons that secrete serotonin. This level is also referred to as *paradoxical sleep* because the sleeper, although exhibiting EEG waves similar to a waking state, is harder to arouse than at any other sleep stage.

2.1.2 NREM

According to 2007 AASM standards, NREM consists of three stages. There is relatively little dreaming in NREM.

Stage N1 refers to the transition of the brain from alpha waves having a frequency of 8–13 Hz (common in the awaken state) to theta waves having a frequency of 4–7 Hz. This stage is sometimes referred to as somnolence or drowsy sleep. Sudden twitches and hypnic jerks, also known as positive myoclonus, may be associated with the onset of sleep during N1. Some people may also experience hypnagogic hallucinations during this stage. During N1, the subject loses some muscle tone and most conscious awareness of the external environment.

Stage N2 is characterized by sleep spindles ranging from 11 to 16 Hz (most commonly 12–14 Hz) and K-complexes. During this stage, muscular activity as measured by EMG decreases, and conscious awareness of the external environment disappears. This stage occupies 45–55% of total sleep in adults.

Stage N3 (deep or slow-wave sleep) is characterized by the presence of a minimum of 20% delta waves ranging from 0.5–2 Hz and having a peak-to-peak amplitude >75 μV. (EEG standards define delta waves to be from 0 to 4 Hz, but sleep standards in both the original R&K, as well as the new 2007 AASM guidelines have a range of 0.5–2 Hz.) This is the stage in which parasomnias such as night terrors, nocturnal enuresis, sleepwalking, and somniloquy occur. Many illustrations and descriptions still show a stage N3 with 20–50% delta waves and a stage N4 with greater than 50% delta waves; these have been combined as stage N3.

2.1.3 Microsleep

A microsleep (MS) is a temporary episode of sleep which may last for a fraction of a second or up to thirty seconds where an individual fails to respond to some arbitrary sensory input.[1][2] MSs occur when an individual loses awareness and subsequently gains awareness after a brief lapse in consciousness, or when there are sudden shifts between states of wakefulness and sleep. In behavioral terms, MSs manifest as droopy eyes, slow eyelid-closure, and head nodding.[23] In electrical terms, microsleeps are often classified as a shift in electroencephalography (EEG) during which 4–7 Hz (theta wave) activity replaces the waking 8–13 Hz (alpha wave) background rhythm.[24]

MSs often occur as a result of sleep deprivation, though normal non-sleep deprived individuals can also experience MSs during monotonous tasks.[25] Some experts define microsleep according to behavioral criteria (head nods, drooping eyelids, etc.), while others rely on EEG markers.[26] Since there are many ways to detect MSs in a variety of contexts there is little agreement on how best to identify and classify microsleep episodes.

Microsleeps become extremely dangerous when they occur in situations that demand constant alertness, such as driving a motor vehicle or working with heavy machinery. People who experience microsleeps usually remain unaware of them, instead believing themselves to have been awake the whole time, or to have temporarily lost focus.[27]

2.1.4 Significance of Microsleep

With over 1,550 fatalities and 40,000 nonfatal injuries occurring annually in the United States alone as a result of drowsy driving, sleep loss has become a public health problem there.[28][29] When experiencing microsleeps while driving an automobile, from the perspective of the driver, he or she drives a car, and then suddenly realizes that several seconds have passed by unnoticed. It is not obvious to the driver that he or she was asleep during those missing seconds, although this is in fact what happened. The sleeping driver is at very high risk for having an accident during a microsleep episode.[30]

Historically, many accidents and catastrophes have resulted from microsleep episodes in these circumstances.[31] For example, a microsleep episode is claimed to have been one factor contributing to the Waterfall train disaster in 2003; the driver had a heart attack and the guard who should have reacted to the train's increasing speed is said by his defender to have microslept, thus causing him to be held unaccountable. On May 31, 2009, an Air France plane (Air France Flight 447) carrying 228 people from Brazil to France crashed into the Atlantic Ocean, killing everyone on board. The pilot of the plane reported "I didn’t sleep enough last night. One hour – it’s not enough," handing over control to the two co-pilots who did not respond appropriately when the plane was in distress.[32][33]

Thus, microsleeps are often examined in the context of driver drowsiness detection and prevention of work-related injuries and public safety incidents (e.g. truck crashes, locomotive crashes, airplane crashes, etc.). Some statistics are below:

- 44% of drivers during late-night driving become dangerously sleepy.[34]
- Extremely fatiguing work protocols increase accident probability from near 0% to 35%.[35]
- Chronic microsleeps (MSs) not only increase probability for injury but also decrease worker productivity and increase likelihood for absenteeism from work.[36]
- According to one CDC (Centers for Disease Control and Prevention) study, among 74,571 adult respondents in 12 U.S. states, 35.3% reported <7 hours of sleep during a typical 24-hour period, 48.0% reported snoring, 37.9% reported unintentionally

falling asleep during the day at least once in the preceding month, and 4.7% reported nodding off or falling asleep while driving at least once in the preceding month.[28]

- The National Highway Traffic Safety Administration estimates that 2.5% of fatal crashes and 2% of injury crashes involve drowsy driving.[37]
- Fatigue is associated with 250 fatalities in air carrier accidents in last 16 years[38]

2.1.5 Neural Correlates

Generally, micro-sleeps are characterized by a decrease in activity in wakefulness-related regions of the brain and an increase in activity in sleep-related regions of the brain. Looking at neural correlates of microsleeps is difficult because microsleeps can also be triggered by monotonous tasks (e.g. such as driving or dozing off in class). Therefore, it is important to examine neural correlates of microsleep events with respect to experimental set-ups (e.g. simulated driving set-up, reaction time set-up, etc.). Individual variability in brain structure also makes it difficult to diagnose microsleep events objectively.

Another study examined the activation patterns of 5 people who woke up from microsleeps in a simulated driving experiment.[39] It was found that upon awakening the visual area, frontal cortex, limbic lobe were activated (in the intense activation phase) and the frontal cortex, temporal cortex, primary motor area, and insula were activated (in the post abrupt awakening phase). Therefore, the study concluded that decision-making was not activated immediately upon waking up from a MS episode, likely increasing risk of injury in intense decision-making tasks like driving or surgery.

The transition from wakefulness to sleep is regulated by a variety of chemicals. Dopamine likely causes the 'feeling sleepy' side of microsleeps, while adenosine likely reduces microsleep events by promoting wakefulness.

2.1.6 Detection methods and classifications

There are currently many ways to detect microsleeps; however, there is a lack of general consensus as to the best way to identify and classify microsleeps. The simplest methods to detect these events seem to be through psychological tests, speech tests, and behavioral tests (e.g. yawn test and eye-video test). More complex and expensive ways to detect microsleeps include EEG, fMRI, EOG, and PSG tied to various software platforms. When multiple tests are used in parallel, detection of microsleeps most likely will become more accurate.[23]

Table 2.1: Methods of microsleep detection

Method	Description or examples
Polysomnography (PSG)	PSG monitors many body functions including brain (EEG), eye movements (EOG), muscle activity or skeletal muscle activation (EMG) and heart rhythm (ECG) during sleep.
Electroencephalography (EEG)	EEG records the brain's spontaneous electrical activity over a short period of time, usually 20–40 minutes, as recorded from multiple electrodes on the scalp.[40] Microsleeps have EEG shift to slower frequencies (from alpha to theta waves).[41]
Functional magnetic resonance imaging (fMRI)	A functional neuroimaging procedure using MRI technology that measures brain activity by detecting associated changes in blood flow (detects what regions of brain are active during microsleep events).[42]
Psychological tests	Reaction time test, Karolinska Sleepiness Scale (KSS),[43] Maintenance of Wakefulness Test (MWT),[44]Multiple Sleep Latency Test (MSLT).[45]
Electrooculogram (EOG)	EOG is a technique for measuring the resting potential of the retina in the human eye.[46]
Eye-video test	Measures eyes blinking and eye movements to detect microsleep events.[47][48]
Mouth yawning test	Counts number of yawns over a period of time.[30]
Speech tests	Examines emotions and/or prosody in speech to predict microsleep episodes.[43][50][51]

2.2 EEG

The electroencephalogram (EEG) measures the activity of large numbers (populations) of neurons. EEG was first recorded by Hans Berger in 1929.

EEG recordings are noninvasive, painless, do not interfere much with a human subject's ability to move or perceive stimuli, are relatively low-cost.

Electrodes measure voltage-differences at the scalp in the microvolt (μV) range. Voltage-traces are recorded with millisecond resolution – great advantage over brain imaging (fMRI or PET).

2.2.1 History

In 1929, Hans Berger

- Recorded brain activity from the closed skull
- Reportet brain activity changes according to the functional state of the brain
  - Sleep
  - Hypnothesis
  - Pathological states (epilepsy)

Figure 2.1: First EEG recorded by Berger

Table 2.2: History of EEG

1875	Caton records brain potentials from cortex
1883	Marxow discovers evoked potentials
1929	Berger records electrical activity from the skull
1936	Gray Walter finds abnormal activity with tumors
1957	The toposcope (imaging of electrical brain activity)
1980	Color brain mapping (quantitative EEG)

In 1957, Gray Walter

- Makes recordings with large numbers of electrodes
- Visualizes brain activity with the toposcope
- Shows that brain rhythms change according to the mental task demanded

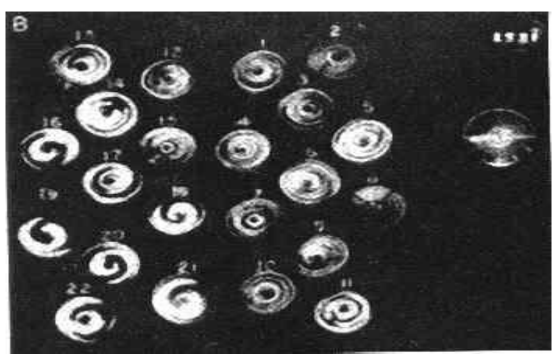

Figure 2.2: The toposcope by Gray Walter

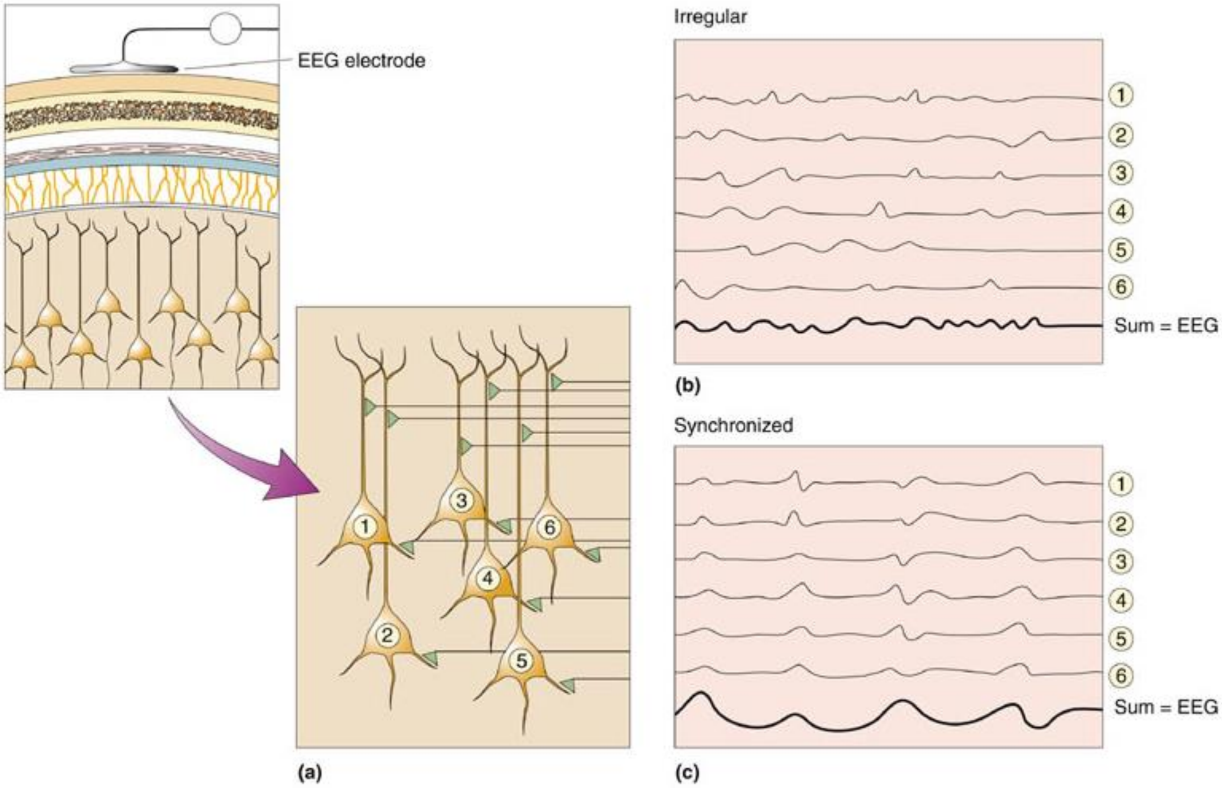

Figure 2.3: Combined activity of the neurons

Many neurons need to sum their activity in order to be detected by EEG electrodes. The timing of their activity is crucial. Synchronized neural activity produces larger signals.

2.2.2 Comparison table of EEG rhythmic activity frequency bands

Table 2.3: Comparison of EEG bands

Band	Frequency (Hz)	Location	Normally
Delta	< 4	frontally in adults, posteriorly in children; high-amplitude waves	• adult slow-wave sleep • in babies • during some continuous-attention tasks[42]
Theta	4 – 7	Found in locations not related to task at hand	• higher in young children • drowsiness in adults and teens • idling • situations where a person is actively trying to repress a response or action[52]
Alpha	8 – 15	Posterior regions of head, both sides, higher in amplitude on non-dominant side. Central sites (c3-c4) at rest	• relaxed/reflecting • closing the eyes • Inhibition control, seemingly with the purpose of timing inhibitory activity in different locations across the brain.
Beta	16 – 31	both sides, symmetrical distribution, most evident frontally; low-amplitude waves	• range span: active calm -> intense -> stressed -> mild obsessive • active thinking, focus, hi alert, anxious
Gamma	32 +	Somatosensory cortex	• Displays during cross-modal sensory processing (perception that combines two different senses, such as sound and sight)[53][54] • Also is shown during short-term memory matching of recognized objects, sounds, or tactile sensations
Mu	8 – 12	Sensorimotor cortex	• Shows rest-state motor neurons.[55]

2.2.3 Wave patterns

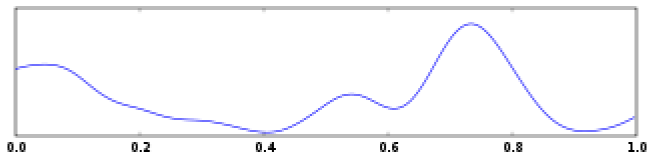

Figure 2.4: Delta waves

Delta is the frequency range up to 4 Hz. It tends to be the highest in amplitude and the slowest waves. It is seen normally in adults in slow wave sleep. It is also seen normally in babies. It may occur focally with subcortical lesions and in general distribution with diffuse lesions, metabolic encephalopathy hydrocephalus or deep midline lesions. It is usually most prominent frontally in adults (e.g. FIRDA - Frontal Intermittent Rhythmic Delta) and posteriorly in children (e.g. OIRDA - Occipital Intermittent Rhythmic Delta).

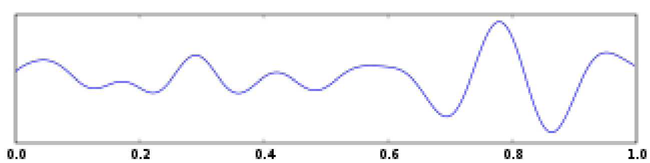

Figure 2.5: Theta waves

Theta is the frequency range from 4 Hz to 7 Hz. Theta is seen normally in young children. It may be seen in drowsiness or arousal in older children and adults; it can also be seen in meditation.[47] Excess theta for age represents abnormal activity. It can be seen as a focal disturbance in focal subcortical lesions; it can be seen in generalized distribution in diffuse disorder or metabolic encephalopathy or deep midline disorders or some instances of hydrocephalus. On the contrary this range has been associated with reports of relaxed, meditative, and creative states.

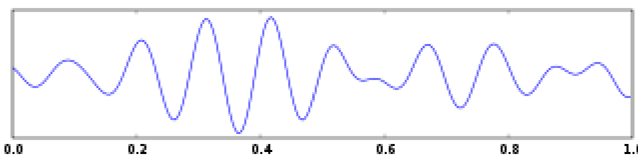

Figure 2.6: Alpha waves

Alpha is the frequency range from 7 Hz to 14 Hz. Hans Berger named the first rhythmic EEG activity he saw as the "alpha wave". This was the "posterior basic rhythm" (also called the "posterior dominant rhythm" or the "posterior alpha rhythm"), seen in the posterior regions of the head on both sides, higher in amplitude on the dominant side. It emerges with closing of the eyes and with relaxation, and attenuates with eye opening or mental exertion. The posterior basic rhythm is actually slower than 8 Hz in young children (therefore technically in the theta range).

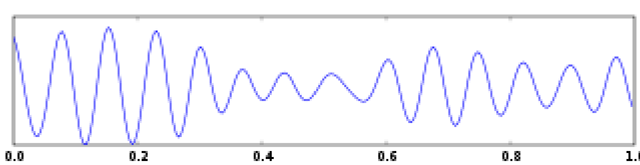

Figure 2.7: Sensorimotor rhythm (mu rhythm)

In addition to the posterior basic rhythm, there are other normal alpha rhythms such as the mu rhythm (alpha activity in the contralateral sensory and motor cortical areas) that emerges when the hands and arms are idle; and the "third rhythm" (alpha activity in the temporal or frontal lobes).[58][59] Alpha can be abnormal; for example, an EEG that has diffuse alpha occurring in coma and is not responsive to external stimuli is referred to as "alpha coma".

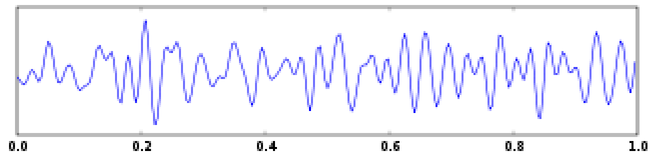

Figure 2.8: Beta waves

Beta is the frequency range from 15 Hz to about 30 Hz. It is seen usually on both sides in symmetrical distribution and is most evident frontally. Beta activity is closely linked to motor behavior and is generally attenuated during active movements.[60] Low amplitude beta with multiple and varying frequencies is often associated with active, busy or anxious thinking and active concentration. Rhythmic beta with a dominant set of frequencies is associated with various pathologies and drug effects, especially benzodiazepines. It may be absent or reduced in areas of cortical damage. It is the dominant rhythm in patients who are alert or anxious or who have their eyes open.

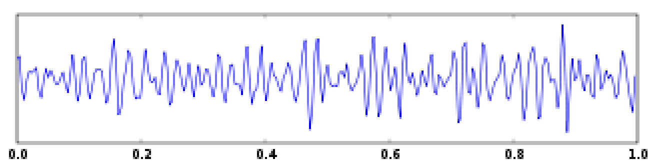

Figure 2.9: Gamma waves

Gamma is the frequency range approximately 30–100 Hz. Gamma rhythms are thought to represent binding of different populations of neurons together into a network for the purpose of carrying out a certain cognitive or motor function.[61]

Mu ranges 8–13 Hz, and partly overlaps with other frequencies. It reflects the synchronous firing of motor neurons in rest state. Mu suppression is thought to reflect motor mirror neuron systems, because when an action is observed, the pattern extinguishes, possibly because of the normal neuronal system and the mirror neuron system "go out of sync", and interfere with each other.[56]

2.2.4 Various Uses

The EEG has been used for many purposes besides the conventional uses of clinical diagnosis and conventional cognitive neuroscience. An early use was during World War II by the U.S. Army Air Corps to screen out pilots in danger of having seizures;[62] long-term EEG recordings in epilepsy patients are still used today for seizure prediction. Neuro-feedback remains an important extension, and in its most advanced form is also attempted as the basis of brain computer interfaces. The EEG is also used quite extensively in the field of neuro-marketing.

The EEG is altered by drugs that affect brain functions, the chemicals that are the basis for psychopharmacology. Berger's early experiments recorded the effects of drugs on EEG. The science of pharmaco-electroencephalography has developed methods to identify substances that systematically alter brain functions for therapeutic and recreational use.

Honda is attempting to develop a system to enable an operator to control its Asimo robot using EEG, a technology it eventually hopes to incorporate into its automobiles.[63]

EEGs have been used as evidence in criminal trials in the Indian state of Maharastra.[64][65]

2.2.5 10-20 system (EEG)

The 10–20 system or International 10–20 system is an internationally recognized method to describe and apply the location of scalp electrodes in the context of an EEG test or experiment. This method was developed to ensure standardized reproducibility so that a subject's studies could be compared over time and subjects could be compared to each other. This system is based on the relationship between the location of an electrode and the underlying area of cerebral cortex. The "10" and "20" refer to the fact that the actual distances between adjacent electrodes are either 10% or 20% of the total front–back or right–left distance of the skull.

Each site has a letter to identify the lobe and a number to identify the hemisphere location. The letters F, T, C, P and O stand for frontal, temporal, central, parietal, and occipital lobes, respectively. Note that there exists no central lobe; the "C" letter is used only for identification purposes. A "z" (zero) refers to an electrode placed on the midline. Even numbers (2, 4, 6, 8) refer to electrode positions on the right hemisphere, whereas odd numbers (1, 3, 5, 7) refer to those on the left hemisphere. In addition, the letter codes A, Pg and Fp identifies the earlobes, nasopharyngeal and frontal polar sites respectively.

Two anatomical landmarks are used for the essential positioning of the EEG electrodes: first, the nasion which is the distinctly depressed area between the eyes, just above the bridge of the nose; second, the inion, which is the lowest point of the skull from the back of the head and is normally indicated by a prominent bump.

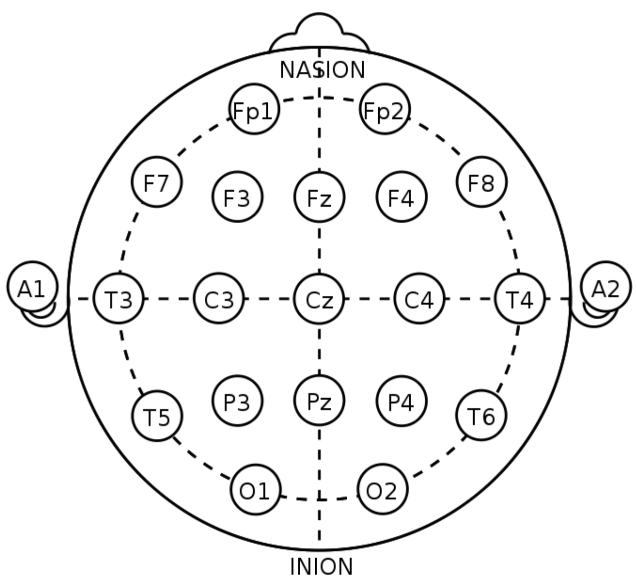

Figure 2.10: Electrode placement for 10-20 system

2.3 Ongoing Research

Detection of drowsiness while driving or doing other tasks that require high level of attention is subject to substantial ongoing research. Literature in this matter helped us decide how we are going to approach in detection of drowsiness.

2.3.1 E. Malar *et al* (2011)[75]

It uses power spectral density of EEG for detection of drunken driving. Though his study was to detect drunken state their proposed system matches our concept and ideas to a certain extent. Since alcohol affects the neural activity of the brain, alpha activity decreases and theta activity increases. In this study a smart cap consisting of five embedded electrode is used to acquire EEG signal. Here the EEG signal is transferred to a microprocessor through Bluetooth where signal processing and analysis is done for alcohol activity. Using stationary wavelet transform time-frequency analysis is performed to decompose the signal in different frequency bands. In these frequency bands they performed power spectral density to find out the power of the signal with significant differences.

In this study they proposed a system consisting of 3 different units:

- Interface Unit
- Digital Pre-Processing Unit
- Intelligence Unit

This system is going to be interfaced with the engine of the car through a relay system which is going to replace the key.

What we want to achieve through our study is the practical implementation of this sort of system, but instead of drunken state we want to detect the drowsy state of a driver.

2.3.2 Seeing Machines-Driver State System [67]

Seeing Machines has won a $1.5 million order for its Driver State System which uses driver eye tracking technology to monitor fatigue.

This system uses driver eye tracking system to monitor the fatigue. It is actually a combination of eye tracking and facial recognition technique to detect driver fatigue. A camera is mounted on the dashboard to track the driver's eye, facial movement and head position.

This system tracks drowsiness, tracks micro-sleep and ensures focus of drivers. It uses In-cabin mitigation technique to alert using audio alert and seat vibrations.

Here in case of eye tracking two or more methods are involved such as

- Eye-Lid tracking or Blink Detection
- Eye Localization

We intend to take inspiration from this work and work for our own algorithm using EEG signal to detect drowsy driving and if possible combining it with this sort of eye-tracking system to make it more efficient.

2.3.3 Kohji Murata *et al* (2011) [66]

It uses non-invasive biological sensor system for detection of drunk driving. In this study different bio-signals are used, so different bio-sensors are required.

Here using air-pack sensors body-trunk plethysmogram and respiration from the back of the driver is detected and used for detection process. These sensors are non-invasive non-confining method implemented in the driver seat. This extracted body-trunk plethysmogram which is also known as air-pack pulse wave is used for detection of alcohol impaired driving.

In this study time-series analysis of frequency fluctuation is conducted. Savitsky and Golay a smoothing filter is used to find the maximum value in the time-series. Here peaks every 5 seconds are determined and reciprocal of the time between peaks is determined and denoted as f. Now the mean of this frequency is calculated.

Here Heart Rate Variability is also kept measure of, yet no significant change is observed. There are certain limitations in implementing this study such as

- Without baseline, data cannot be distinguished between normal and intoxicated state.
- Long-time measurement required.

2.3.4 Christos Papadelis *et al* (2006) [69]

It's a study of indicators of sleepiness using EEG at night driving. It is an EEG based method assessing significant brain activity alterations induced by drivers' drowsiness. In this study Relative Band Ratio (RBR) of different frequency bands, Shanon Entropy and Kullback-leibler Entropy were estimated from the acquired EEG signal.

Since EEG reflects the effects of sleepiness to central nervous system, it has been proposed to be the best sleepiness indicator. More Importantly previous studies have shown that Alpha and theta bands are more prone to sleepiness.

In his study scientists used 3rd order Butterworth filter and Info Independent Component Analysis (I-ICA) technique in order to remove eye movements and eye blinks. Thus analysis was performed without any artifacts.

A significant increase of alpha wave Relative band Ratio and a decrease of gamma wave RBR was observed in this study. A decrease in Shanon and K-L entropy were also observed just before the drowsiness.

2.3.5 Antoine Picot *et al* (2008)[68]

This presents on-line automatic detection of single channel EEG signal. Though the study is for single channel EEG four channel data was recorded (F3, C3, P3, O1)

This study is based on a mean comparison test to detect changes of the relative power of the alpha frequency band (8-12 Hz). Previous studies show that drowsiness is characterized by an increase of alpha and theta activities, predominant in the posterior region of the brain.

In this study two kinds of scales were used

- Subjective sleepiness scales
  For example Karolinska Sleepiness Scale (KSS) – allows drivers to directly evaluate their own drowsiness.
- Objective sleepiness scales

Here detection method is independent of the drivers and doesn't need to be modified depending on person. Here the scientists used EEG power spectral analysis to detect bursts in the EEG activity.

According to this study methods based on neural networks need a huge quality database to train the network. It is also observed that ICA methods need to have a large number of EEG channels.

In short the detection method of this paper:

- STFT-finding relative energy in different energy bands
- Median Filtering
- Mean Comparison test
- Compare the energy to a reference level which is the threshold of detection.

But the problem with this study is that the decision provided by the algorithm is delayed by 20 seconds from the signal recorded.

Chapter 3: Theoretical Background of the Study

3.1 Fast Fourier Transform

DFTs with a million points are common in many applications. Modern signal and image processing applications would be impossible without an efficient method for computing the DFT.

Direct application of the definition of the DFT to a data vector of length n requires n multiplications and n additions—a total of $2n^2$ floating-point operations. To compute a million-point DFT, a computer capable of doing one multiplication and addition every microsecond requires a million seconds, or about 11.5 days.

The fast Fourier transform (FFT) is a discrete Fourier transform algorithm which reduces the number of computations needed for N points from $2N^2$ to $2N\log_2 N$. While Fourier analysis converts time (or space) to frequency and vice versa; an FFT rapidly computes such transformations by factorizing the DFT matrix into a product of sparse (mostly zero) factors. As a result, fast Fourier transforms are widely used for many applications in engineering, science, and mathematics.

In MATLAB, the functions Y = fft(x) and y = ifft(X) implement the transform and inverse transform pair given for vectors of length N by:

Equation 3.1: FFT

$$X(k) = \sum_{j=1}^{N} x(j) e^{-\frac{2\pi i}{N}(j-1)(k-1)}$$

Equation 3.2: IFFT

$$x(j) = \frac{1}{N} \sum_{k=1}^{N} X(k) e^{-\frac{2\pi i}{N}}$$

3.2 Power Spectral density

Spectral analysis is a mathematical approach to quantify the EEG. It does not provide a biophysical model of EEG generation. Its purpose is the decomposition of signals such as the EEG, into its constituting frequency components.
The power density spectrum or power spectrum displays the distribution of power or variance over the frequency components of a signal. It is defined as the Fourier transform of the autocorrelation function.

In practical applications, spectra are estimated by the discrete Fourier transformation based on data of finite length. Power density spectra can be estimated by the "periodogram method"[11]. To this effect, the signal is divided into segments, which may overlap. These segments are weighted (multiplied) by a non-rectangular window function to reduce edge effects (leakage) prior to the FFT. The FFT results in a complex spectrum. The absolute values are squared to obtain power density values. To estimate the power density spectrum it is advisable to average over several segments or smooth over frequency bins in order to reduce the variance of the estimate.

The units of power density values are expressed either in V^2/Hz or μV^2/Hz when looking at broad bands. While taking into account the frequency resolution, the resulting units of power are V^2 or μV^2.

The power spectrum of a time-series x(t) describes how the variance of the data x(t) is distributed over the frequency components into which x(t) may be decomposed. This distribution of the variance may be described either by a measure μ or by a statistical cumulative distribution function S(f) the power contributed by frequencies from 0 up to f.

Thus Power Spectral Density is the Fourier Transform of the autocorrelation function of a signal. First compute the auto correlation function and then compute its Fourier Transform. Power spectral density describes the signal power distribution over the frequency.

3.3 The Trapezium Rule

The trapezium rule is a way of estimating the area under a curve. We know that the area under a curve is given by integration, so the trapezium rule gives a method of estimating integrals. This is useful when we come across integrals that we don't know how to evaluate.

The trapezium rule works by splitting the area under a curve into a number of trapeziums, which we know the area of.

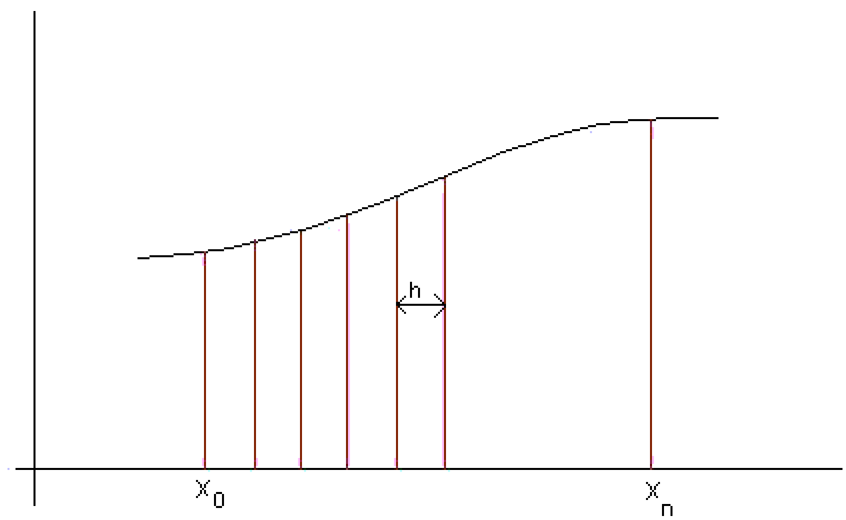

Figure 3.1: Splitting of area under a curve for trapezium rule

If we want to find the area under a curve between the points x_0 and x_n, we divide this interval up into smaller intervals, each of which has length h (see diagram above).

Then we find that:

Equation 3.3: Trapezium Rule

$$\int_{x_0}^{x_n} f(x)\,dx = \frac{h}{2}[(y_0 + y_n) + 2(y_1 + y_2 + \cdots + y_{n-1})]$$

Where $y0 = f(x0)$, $y1 = f(x1)$, … etc.

If the original interval was split up into n smaller intervals, then h is given by: $h = (x_n - x_0)/n$

3.4 PhysioBank

PhysioBank is a large and growing archive of well-characterized digital recordings of physiologic signals and related data for use by the biomedical research community. PhysioBank currently includes databases of multi-parameter cardiopulmonary, neural, and other biomedical signals from healthy subjects and patients with a variety of conditions with major public health implications, including sudden cardiac death, congestive heart failure, epilepsy, gait disorders, sleep apnea, and aging.

PhysioBank currently contains over 40,000 recordings of annotated, digitized physiologic signals and time series, organized in over 60 databases (collections of recordings) which are freely available from PhysioNet.

Many of the databases currently in the PhysioBank Archives were developed at MIT and at Boston's Beth Israel Hospital (now the Beth Israel Deaconess Medical Center). All of these databases are available in their entirety from these archives. The support provided to PhysioBank by the NIH makes it possible for us to provide free access to these databases via PhysioNet to the research community.

For our study and signal processing, we used the EEG signals from “Sleep-EDF Database [Expanded] (sleep-edfx)”

3.5 EEGLAB

EEGLAB is an interactive MATLAB toolbox for processing continuous and event-related EEG, MEG and other electrophysiological data incorporating independent component analysis (ICA), time/frequency analysis, artifact rejection, event-related statistics, and several useful modes of visualization of the averaged and single-trial data.

3.5.1 Why EEGLAB?

EEGLAB provides an interactive graphic user interface (GUI) allowing users to flexibly and interactively process their high-density EEG and other dynamic brain data using independent component analysis (ICA) and/or time/frequency analysis (TFA), as well as standard averaging methods. EEGLAB also incorporates extensive tutorial and help windows, plus a command history function that eases users' transition from GUI-based data exploration to building and running batch or custom data analysis scripts. EEGLAB offers a wealth of methods for visualizing and modeling event-related brain dynamics, both at the level of individual EEGLAB 'datasets' and/or across a collection of datasets brought together in an EEGLAB 'study set.'

3.5.2 EEGLAB Features

- Graphic user interface
- Multi format data importing
- High-density data scrolling
- Defined EEG data structure
- Open source plug-in facility
- Interactive plotting functions
- Semi-automated artifact removal
- ICA & time/frequency transforms
- Many advanced plug-in toolboxes
- Event & channel location handling
- Forward/inverse head/source modeling

3.6 Nicolet v32 Workstation

We used Nicolet EEG v32 workstation to acquire raw EEG signal for our experiment. We used a single channel to acquire EEG signal.

Nicolet EEG v32/v44 (workstation) optimizes one software platform allow use as needed, (routine procedures, epilepsy monitoring, critical care, pre and post-op, status epilepticus, stroke, sleep disorders, stat procedures, etc) and can maximize efficiencies. These products offer high-quality diagnostic information in easy-to-use, customizable formats.

3.6.1 System features

- One modular neuro-diagnostic system performs procedures for EEG, ICU, LTM, OR, Sleep, NCS, EP and EMG testing
- High quality Ethernet amplifiers
- Central monitoring provides up to four patient views with video on a single display
- Various Headbox options
- Various installation options including fixed rooms, cart systems, laptops and ambulatory
- Synchronized EEG and video with software-controlled camera

In this experiment we used one electrode at Fp2 and another electrode at A1.

Chapter 4: Signal Processing & Data Analysis

4.1 PhysioBank data

We acquired our data from the PhysioBank database and imported into MATLAB for processing. To convert the raw units into the physical units, 'base' was subtracted from the signal data and then it was divided by 'gain'. Both base and gain parameter for each and every signal were specified in the database.

4.1.1 Noise removal

After baseline correction, the EEG signal was filtered to remove high frequency components using a low pass Butterworth filter. By removing the high frequency artifacts, the signal became smoother and was restricted within a 1-40 Hz frequency range.

The reason for this restriction is high frequency indicates higher brain activity which is not our concern for sleep related studies.

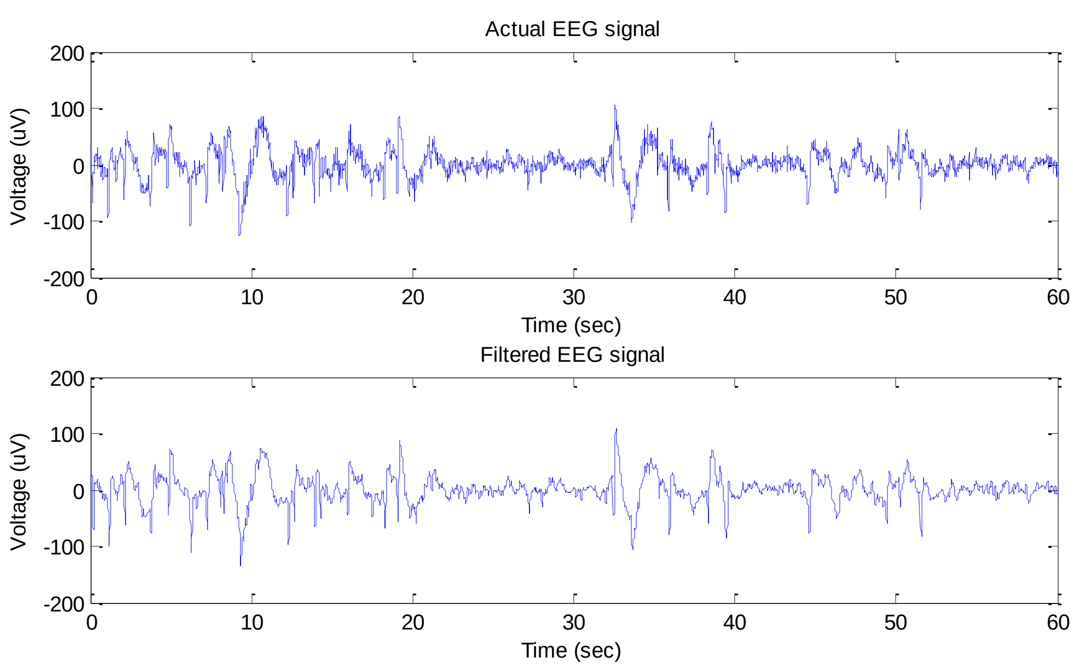

Figure 4.1: Filtering raw EEG signal

4.1.2 Signal processing by FFT

The EEG signals for a sleeping subject (Sleep EEG) and a non-sleeping subject (Normal EEG) are imported into MATLAB. After performing Fast Fourier Transform, we observe the following cases.

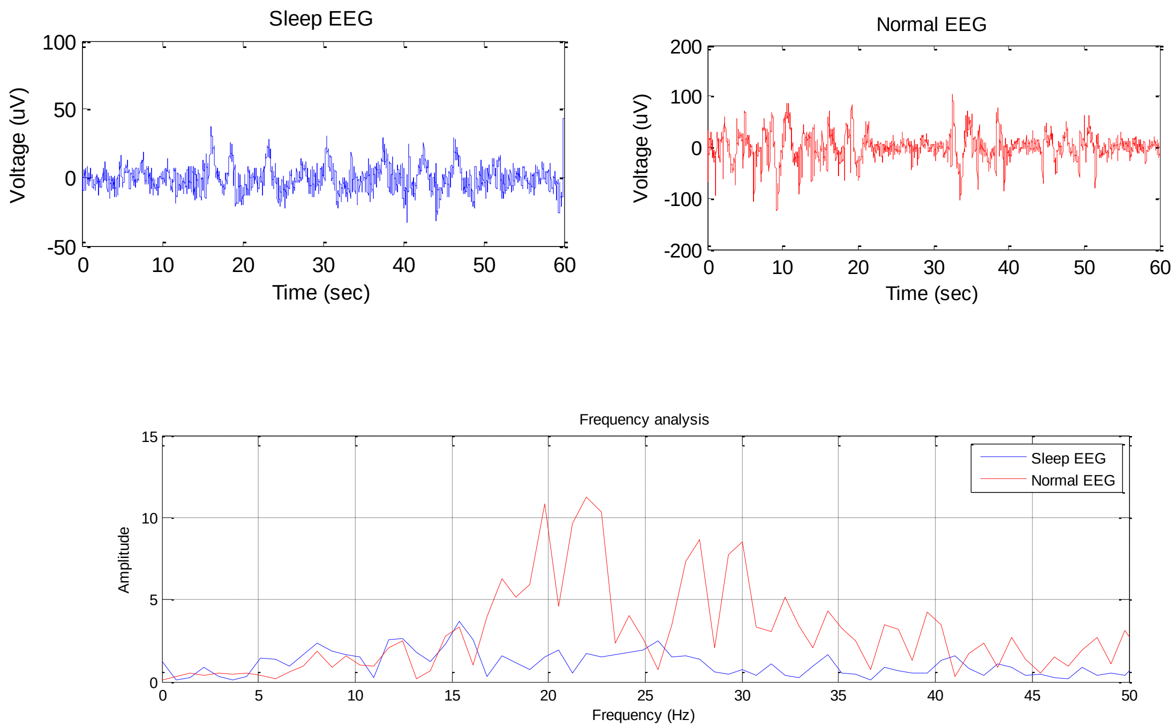

Figure 4.2: Frequency spectrum of sleepy & non-sleepy EEG signal

Clearly we can see that, the frequency spectrum of a non-sleeping person has higher amplitude than a sleeping person.

For the non-sleeping subject, frequencies around 20, 22, 27 and 30 Hz are dominant which are in the **beta band**.

On the contrary, frequencies less than 16 Hz are more dominant for the sleeping subject i.e. **alpha band** is more active.

4.1.3 Signal Processing by EEGLAB

Filtered EEG signals of the subject sleeping and not sleeping, were imported into EEGLAB and the channel power spectral density was calculated. Both the signals were of 10 seconds duration.

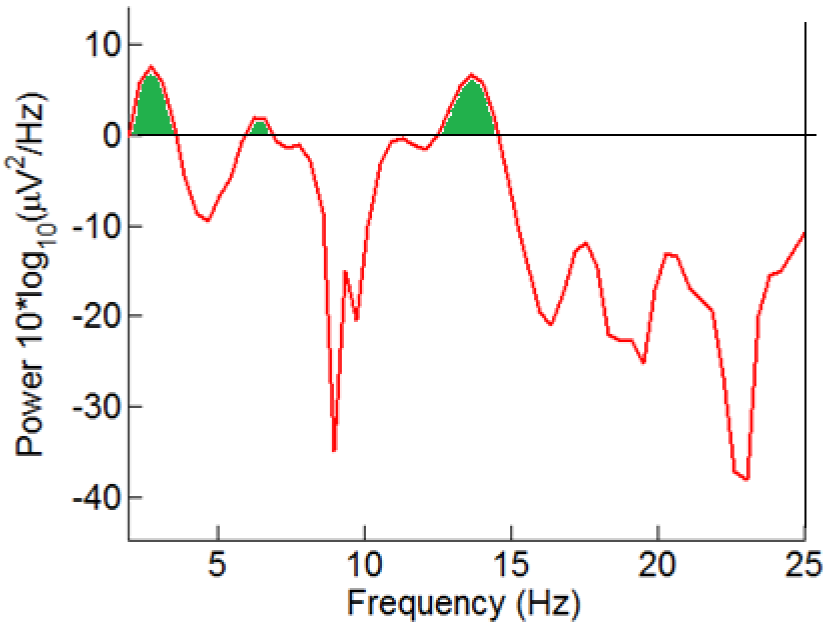

Figure 4.3: Test subject1 - sleeping (10 sec signal)

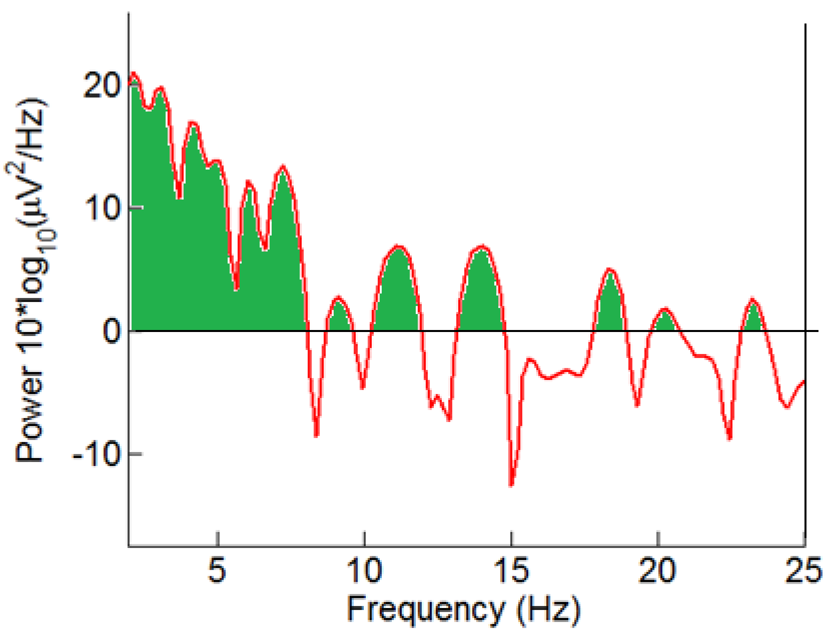

Figure 4.4: Test subject1 - not sleeping (10 sec signal)

Now another set of two EEG signals of the same subject was imported into EEGLAB, both of which were 1 minute long. Here we observe similar case as happened to the 10 seconds long signals; area under the curve and above 0 power level is smaller for sleeping condition.

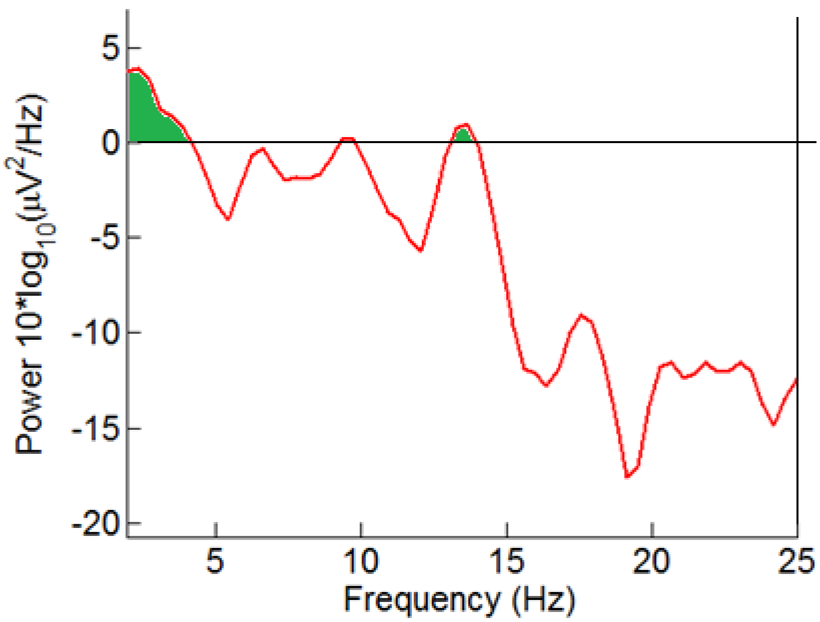

Figure 4.5: Test subject1 - sleeping (1 min signal)

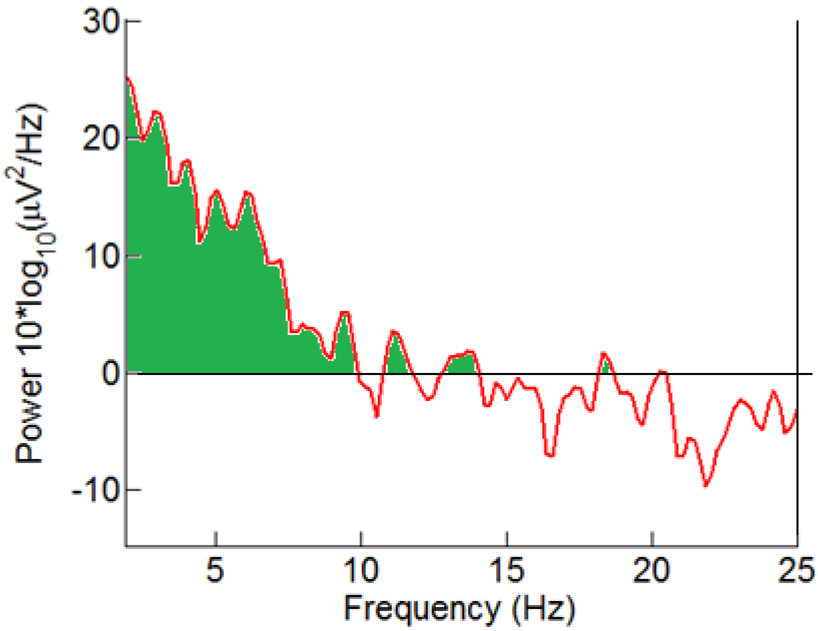

Figure 4.6: Test subject1 - not sleeping (1 min signal)

Now we took the EEG signals of 6 subjects and plotted the channel power spectral density at different times while sleeping. Here each of these graphs is plotted for 10 second long signals.

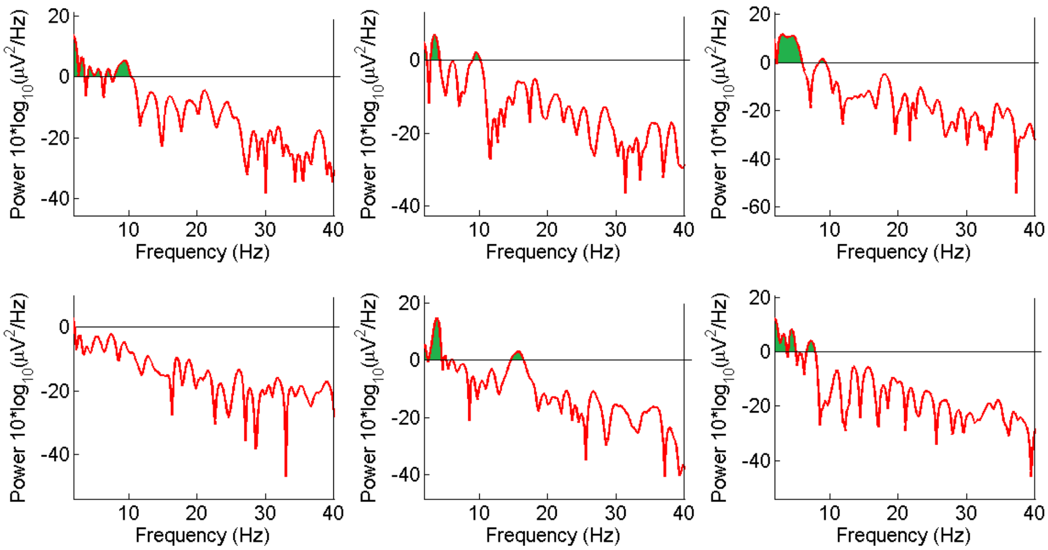

Figure 4.7: Test subjects 2 to 7 - sleeping

Now channel PSD of EEG signal was plotted for the same subjectswhile they were awake.

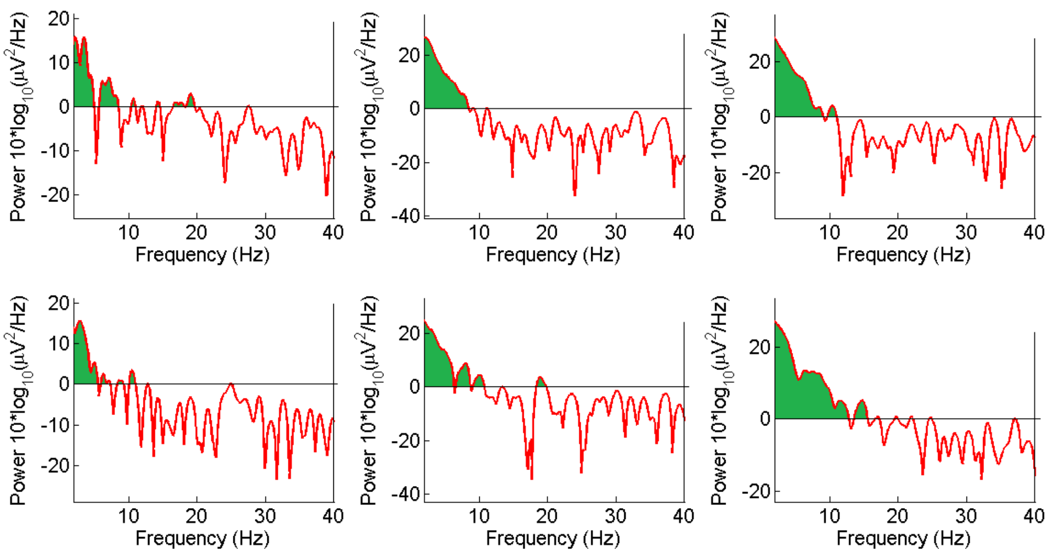

Figure 4.8: Test subjects 2 to 7 - not sleeping

In each case, area under the curve above 0 power level is comparatively small in case of the sleeping subject. When the subject was not sleeping, the area significantly increased.

4.2 Lab acquired data

4.2.1 Noise Removal

Data acquired from the Nicolet v32 EEG workstation contained noise from the 50 Hz AC transmission line. Thus it was necessary to remove the noise before any kind of processing of the signal.

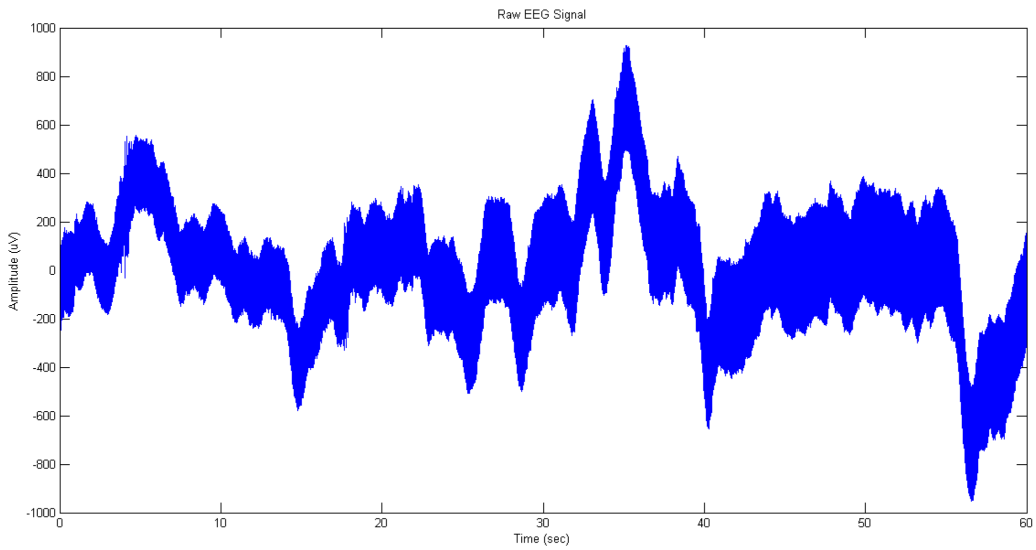

Figure 4.9: Raw EEG signal containing 50 Hz noise from AC line

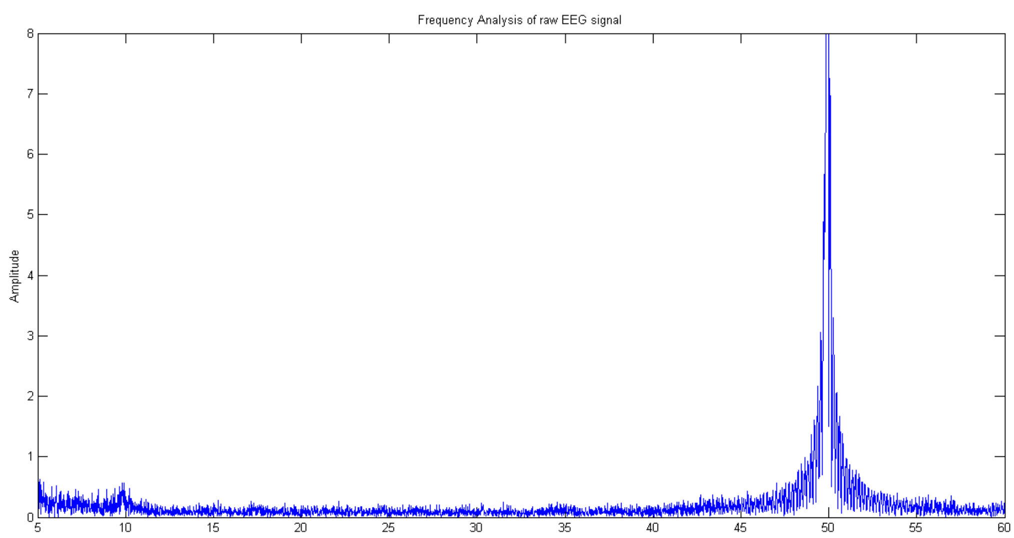

Figure 4.10: Frequency spectrum of the raw EEG signal containing 50 Hz noise

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In order to remove the 50 Hz noise from AC line, a filter with sharp cut off and very small bandwidth limit was needed. This was achieved by using a notch filter which effectively removed the 50 Hz artifact.

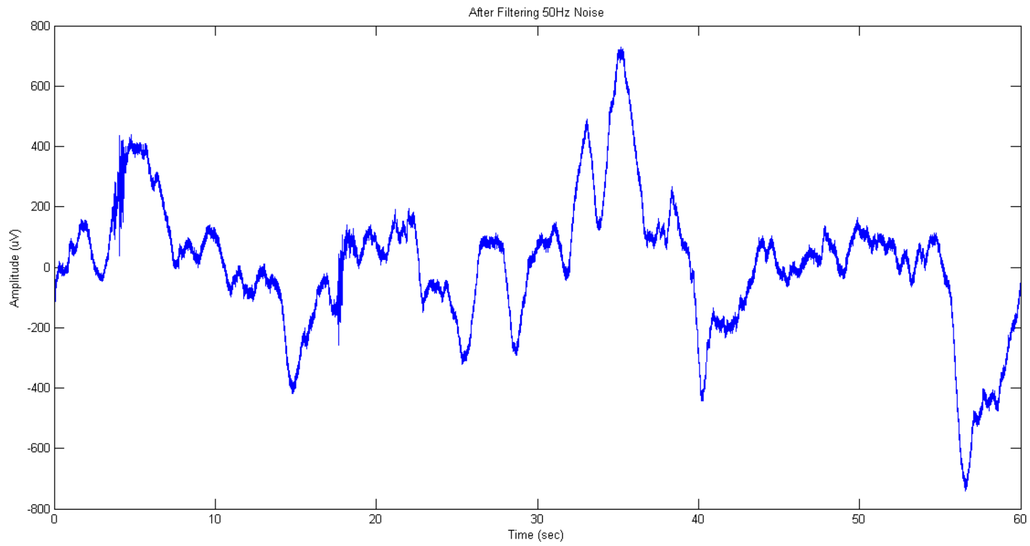


Figure 4.11: Raw EEG signal after removing the 50 Hz noise

4.2.2 Signal Processing by EEGLAB

The raw EEG data after filtering was taken into EEGLAB like we did for PhysioBank data and plotted the channel power spectral density. Here the EEG signals are taken randomly and the duration was 10 seconds for each signal.

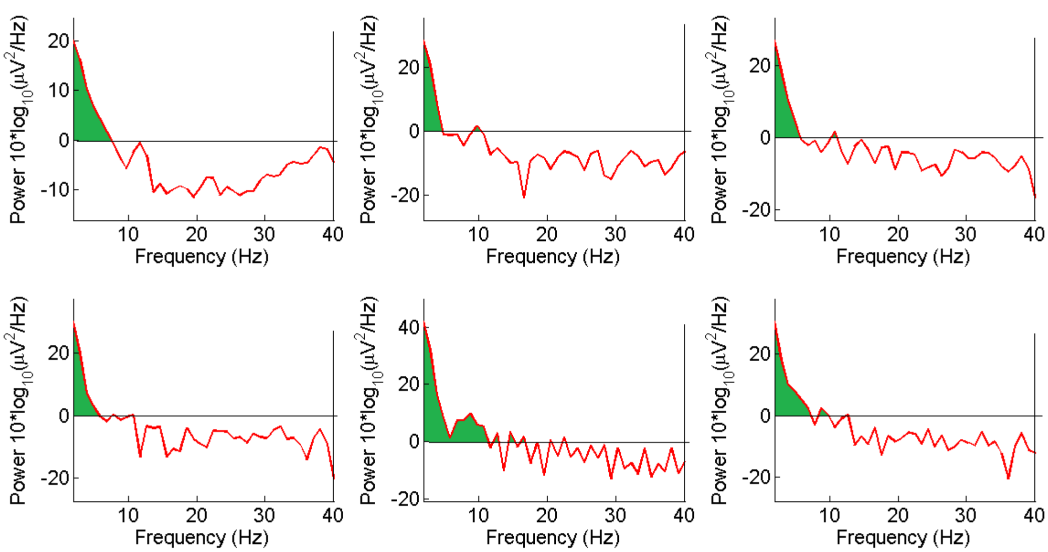


Figure 4.12: Test subject sleeping (data taken from Nicolet v32)

Now we plotted the channel PSD of the EEG signals taken when the test subject was not sleeping. Here also the signal duration was 10 seconds long for each case.

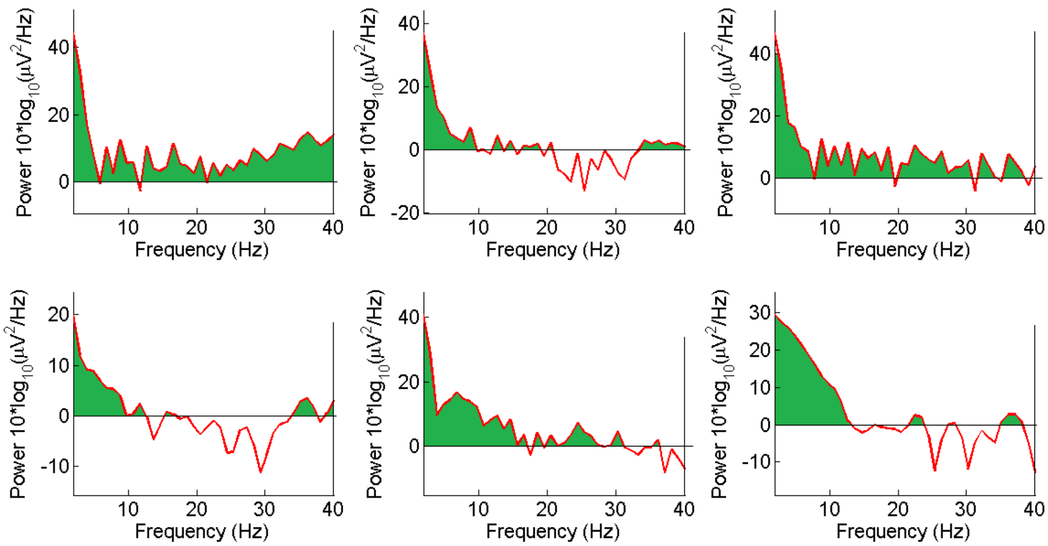


Figure 4.13: Test subject not sleeping (data taken from Nicolet v32)

As we can see from these graphs, we got similar observations to the PhysioBank data from our experimental data.

Similar observations were obtained from another experiment.

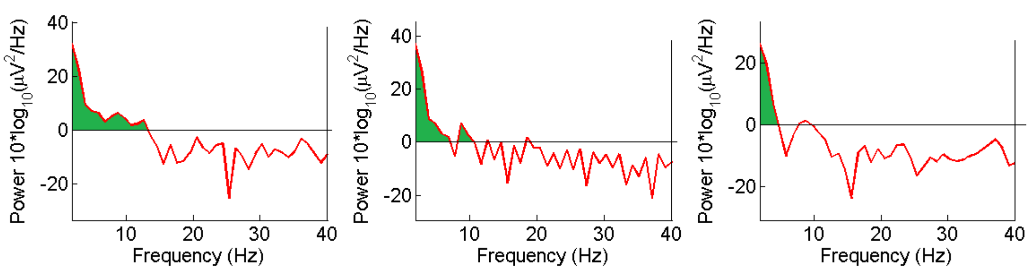


Figure 4.14: Test subject sleeping

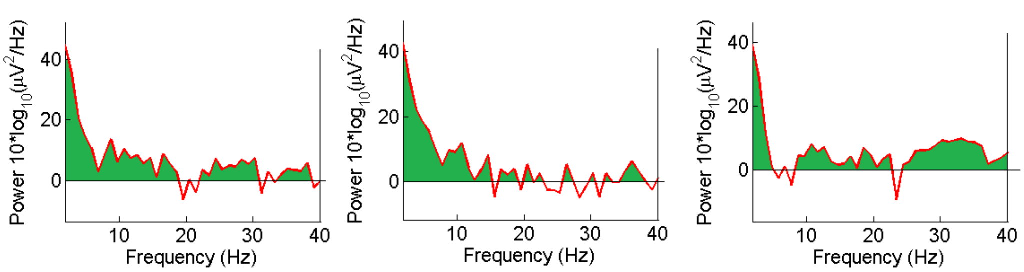
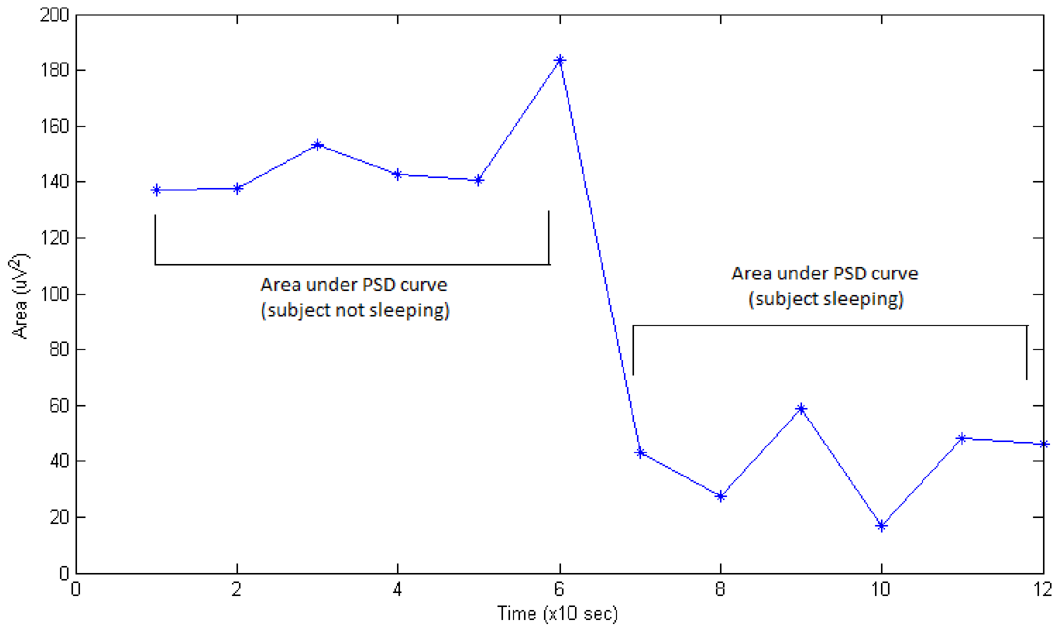


Figure 4.15: Test subject not sleeping

4.2.3 Area calculation

We calculated the area under curves for one subject using trapezoidal formula and plotted it against time interval. This helped us to visualize the change in area over time.



From the above graph, it is clear that there is a significant change in area under PSD curve as the subject's state changes from awake to sleep. Thus we can take proper decision based on these facts.

Chapter 5: Conclusion

5.1 Future Works

Usually wearing any sort of device while driving is uncomfortable, for some drivers it might be a distraction. But now-a-days drivers are used to wearing Bluetooth headsets while driving for receiving emergency calls.

So we are considering to types of EEG data acquisition system

- Using wireless Bluetooth connected EEG headset device
- Using dry- wireless electrodes in the seat of the driver

The EEG headset will also use dry-sensors. So no gel or hair removal is required. It will be an attractive looking device with other facilities present to attract the consumers. The sensors in the seat will communicate through Bluetooth. Research work is still on-going with this sort of system. But definitely this system will be more comfortable for the consumer at least for long drives.

Now-a-days on Android and on cell phones of other platforms, it is very convenient to perform signal processing. Using Bluetooth we can transfer our raw EEG signal to the cellular device and analyze the recordings. Using the same device we can alert the driver using an alarm or vibration.

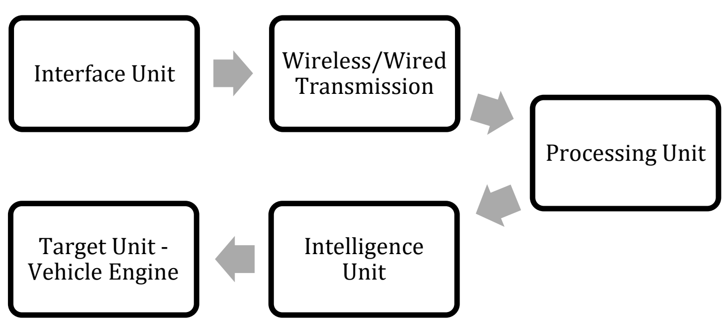


Figure 5.1: Block diagram

Instead of the cellular device we can also use and integrated system combined of micro-processors and filters. It will also work the same way such as receiving data from the EEG device through Bluetooth, then signal filtering and processing. This device can also be integrated to the car engine or some sort of driver warning system for example a very small electric pulse, audio alert or seat vibration.

For integrating the device to the engine of the car we require a relay system which will slow down the car and for longer period of drowsiness bring the car to halt.

We also recommend implementing this system alongside eye tracking and other bio-sensors to be able to compare in real time and perform survey.

5.2 Discussion

It is understandable that in present day drowsy driving plays a huge role in the high-rate of traffic collisions. But only a few group of people pay heed to this fact where as it should be of major concern, since drowsy driving is prevalent and a major health and safety issue.

We visualized a system where we continuously monitor the cognitive status of a driver through EEG and automatically detect drowsiness and micro-sleeps and then take necessary actions. Our work in this study has been related to EEG signal processing so that we can efficiently detect drowsy events with least possible delay.

In this study we found that it is easier to analyze EEG signal using a combination of power spectral density and area calculation rather than other techniques considering different factors such as time delay and amount of data required.

We strongly believe a future is possible where no such drowsy driving accidents will occur, where car manufacturers will use such integrated systems to detect drowsy driving based upon our research, previous studies and more research works in coming years.

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