

Drowsiness Detection Using Preused Database of EEG Sensor for Accident Prevention

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ABSTRACT: A tiredness identification framework utilizing both mind and visual action is exhibited in this paper. The mind action is observed utilizing a solitary electroencephalographic (EEG) channel. An EEG-based sluggishness finder utilizing indicative procedures and Fuzzy rationale is proposed. Visual action is checked through flickering recognition and portrayal. Squinting components are separated from an electrooculographic (EOG) channel. Elements are consolidated utilizing Fuzzy rationale to make an EOG-based sleepiness identifier. The components utilized by the EOG-based indicator are deliberate limited to the elements that can be naturally extricated from a video examination of the same exactness. Both discovery frameworks are then combined utilizing falling choice guidelines as per a therapeutic size of sluggishness assessment. Blending mind and visual data makes it conceivable to distinguish three levels of sluggishness: "conscious," "sleepy," and "exceptionally lazy." One noteworthy point of interest of the framework is that it doesn't need to be tuned for every driver. The framework was tried on driving information from 20 unique drivers and achieved 80.6% right orders on three laziness levels. The outcomes demonstrate that EEG and EOG finders are repetitive: EEG-based location is utilized to affirm EOG-based identification and accordingly empower the false caution rate to be diminished to 5% while the genuine positive rate is not diminished, contrasted and a solitary EOG-based identifier.

KEYWORDS: Blinking analysis, cascading rules decision, drowsiness, electroencephalographic (EEG), electrooculographic (EOG), fuzzy logic.

I. INTRODUCTION

Driver's fatigue has been implicated as a causal factor in many accidents. Preventing such accidents is thus a major focus of efforts in the field of active safety research. A number of methods have been proposed to detect vigilance changes in the past. Even though each driver thinks that he/she can control the vehicle very well at all times, there still are some risks happened due to drivers tiredness, drowsiness, or inattention. Driver drowsiness is an important factor in the motoring of vehicle accidents.^[1] It was demonstrated that driving performance deteriorates with increased drowsiness resulting into crashes constituting more than 20% of all vehicle accidents. Traditional transportation system is no longer sufficient. Recently an artificial intelligence technique has emerged and gaining popularity among transportation researchers.^[2]

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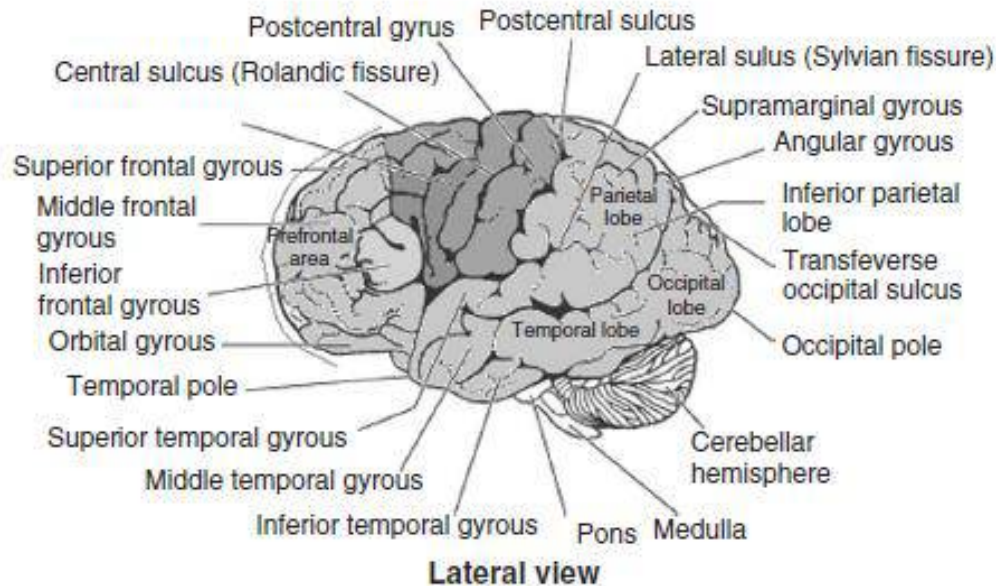


Figure 1: Lateral View of Brain

The brain represents not only the brain function but also the status of the whole body. Electro-(referring to registration of brain electrical activities) encephalo-(referring to emitting the signals from the head), and gram (or graphs), which means drawing or writing, the term EEG is used to denote electrical neural activity of the brain.^[4] An EEG signal is a measurement of currents that flow during synaptic excitations of the dendrites of many pyramidal neurons in the cerebral cortex. When brain cells (neurons) are activated, the synaptic currents are produced within the dendrites. Electroencephalography (EEG) is the recording of electric potentials produced by the local collective partial synchrony of electrical field activity in cortical neuropile, today most commonly measured by an array of electrodes attached to the scalp using water-based gel. EEG is the most widely known and studied portable noninvasive brain imaging modality; another, less developed and not considered here, is functional near-infrared spectroscopy (FNIR). The first report of signals originating in the human brain and recorded non-invasively from the scalp was that of Berger in 1924.^[3] The brain is made of three main parts: the forebrain, midbrain, and hindbrain. The forebrain consists of the cerebrum, thalamus, and hypothalamus (part of the limbic system). The midbrain consists of the tectum and tegmentum. The hindbrain is made of the cerebellum, pons and medulla. Often the midbrain, pons, and medulla are referred to together as the brainstem. The Cerebrum: The cerebrum or cortex is the largest part of the human brain, associated with higher brain function such as thought and action. The cerebral cortex is divided into four sections, called "lobes": the frontal lobe, parietal lobe, occipital lobe, and temporal lobe.^[2] Generators of electric field which can be registered by scalp electrodes are groups of neurons with uniformly oriented dendrites. The neurons permanently receive impulses from other neurons. These signals affect dendritic synapses inducing excitatory and inhibitory postsynaptic potentials. Currents derived from synapses move through the dendrites and cell body to a trigger zone in the axon base and pass through the membrane to the extracellular space along the way. EEG is a result of summation of potentials derived from the mixture of extracellular currents generated by populations of neurons. Hereby the EEG depends on the cytoarchitectures of the neuronal populations, their connectivity, including the feedback loops, and the geometries of their extracellular fields (Freeman 1992).^[4] The appearance of EEG rhythmic activity in scalp recordings is only possible as a result of the synchronized activation of massifs of neurons, the summed synaptic events of which become sufficiently large (Steriade et al 1990). The rhythmic activity may be generated by both pacemaker neurons having inner capability of rhythmic oscillations and neurons which cannot generate a rhythm separately but can synchronize their activity through excitatory and inhibitory connections in such a manner that constitute a network with

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 5, May 2016

pacemaker properties. The latter may be designated as neuronal oscillators (Madler et al 1991; Kasanovich and Borisyuk 1994; Abarbanel et al 1996). The oscillators have their own discharge frequency, various among different oscillators and dependent on their internal connectivity (Figure 1), in spite of close intrinsic electrophysiological properties of single neurons which constitute different oscillators. The neuronal oscillators start to act in synchrony after application of external sensory stimulation (Lopes da Silva 1991; Basar 1992) or hidden signals from internal sources.

II. MOTIVATION

The development of a human bio signal based drowsy state monitoring system for drivers has become a major focusing the field of safety driving and accident prevention because drivers fatigue has been implicated as a causal factor in many car accidents. Accidents caused by drowsiness at the wheel have a high fatality rate because of the marked decline in the Driver's abilities of perception, recognition and vehicle control abilities while sleepy.^[1] Even though each driver thinks that he/she can control the vehicle very well at all times, there still are some risks happened due to drivers tiredness, drowsiness, or inattention. Driver drowsiness is an important factor in the motoring of vehicle accidents. It was demonstrated that driving performance deteriorates with increased drowsiness resulting into crashes constituting more than 20% of all vehicle accidents. Traditional transportation system is no longer sufficient. Recently an artificial intelligence technique has emerged and gaining popularity among transportation researchers. If the real time situations are observed during the constant working environment in industries and while driving vehicles for prolonged hours, humans tend to get very tired and feel fatigued. This fatigue-ness affects their mental state and there comes a point where humans do lose control over themselves and fall asleep. While in an industry, they deal with heavy machineries and if a little deviation of attention of theirs can lead to fatal mishaps.^[2] Also, while driving one needs to be quiet attentive as the roads are never empty or straight. Deviating attention due to drowsiness proves to be fatal and so here we have proposed a system, which takes the mental state data, processes them, compares the values with predefined values defined from doctors and generate an alarm or warning for them to have rest or break. To continue with some examples as, Company's business processes may require the service for 24 hours a day. However, this could cause some problems.^[4] For example, a worker lost his hand because of drowsiness while working in a wood cutting machine. A young even lost his life because working in a sleepy condition. Car driving is very prone to accident due to drowsiness. According to Directorate General of Land Transportation, Department of Transportation, accident that occurred is 93.52% caused by drowsiness. Researches for early drowsiness detection have been done by previous researchers. Various methods have been used, such as Carafe, a method based on eye's blink through Computer Vision technology. It utilized camera on a Smartphone. Its accuracy to detect drowsiness was up to 85%.^[1] Drowsiness is the common thing that happens to every human. However, this could cause some problems. There have been many accidents happen, that worker must lose the part of his/her body, disability, and even life because of the drowsiness factor while doing work. In addition to solve this matter, an application is needed to give warning for workers when it detects the drowsiness. By using the brainwave receiver sensor, the application can give early warning in real-time based on worker condition. This research involves subjects were using perused database from EEG & EOG sensors and after doing some feature extraction we can give warning to driver as per level of drowsiness by implementing alarm system or by giving driver some audio message for avoiding accidents.

III. BACKGROUND

A study specifies that every year, about 15% to 20% of car crashes are due to driver drowsiness and prove to be fatal. Drowsiness can be defined as the transition between the awake state and the sleep state where one's ability to observe and analyze are strongly reduced to a great extent. Thus increasing the consequences in reaction time as well as a decrease in driver vivacity which lead to an impairment of driving abilities. Efforts to increase traffic safety have led the research community to focus on the detection of this unsafe state in an automated way. For the last few decades, driver drowsiness has been monitored with two kinds of systems. The first one is "vehicle oriented".^[4] Drowsiness is detected by analyzing the driver's behavior using information measured by sensors located in the vehicle, such as its position on the road, steering wheel movements, pressure on the driving pedals or the variability of the car's speed. The

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 5, May 2016

main disadvantage of this approach is that driving behavior may be very different from one driver to another. This makes it difficult to construct a “correct driving” model that can be used to detect variations in driving behavior. This model has to be learnt for each driver. The second kind of system is the “**driver-oriented**” systems. Drowsiness is detected using physiological information, measured by sensors located on or around the driver (electrodes, camera, etc.) such as cerebral activity, eye activity, facial expressions, yawns, or gaze direction. These driver-oriented systems are more reliable because physiological drowsiness signs are well known and rather similar from one driver to another. However, one drawback with placing sensors on the driver is that they should not bother him.

| Objective sleepiness Score | EEG activity in the α and/or Θ bands | Blinking and eye movements |
|----------------------------|--|----------------------------|
| 0 | Negligible | Normal |
| 1 | Less than 5s | Normal |
| 2 | Less than 5s | Slow |
| 3 | Less than 10s | Slow |
| 4 | More than 10s | Slow |

TABLE 1: OBJECTIVE SLEEPINESS CRITERIA

Other studies have focused on the analysis of visual signs, such as blinking or visual gaze, to detect driver drowsiness. Very good indicators of drowsiness can therefore be extracted from blinking analysis. These signs are traditionally extracted using an electrooculogram (EOG) which measures electrical eye activity. Various classification techniques to detect drowsiness from blinking features such as partial least squares regression-based fusion model or fuzzy fusion have been tested. Blinking analysis can also be processed using a video camera. A recent study showed that some blinking features can be extracted with the same accuracy from a video analysis as from an EOG analysis. Most drowsiness detection systems based on video analysis are nevertheless based on two features: the duration of the blinking and the direction of the gaze. Recent study has suggested using also facial cues such as yawning and eyebrows rising.

IV. LITERATURE SURVEY

Many brain disorders are diagnosed by visual inspection of EEG signals. The clinical experts in the field are familiar with manifestation of brain rhythms in the EEG signals. In healthy adults, the amplitudes and frequencies of such signals change from one state of a human to another, such as wakefulness and sleep. The characteristics of the waves also change with age. There are five major brain waves distinguished by their different frequency ranges. These frequency bands from low to high frequencies respectively are called alpha (α), theta (θ), beta (β), delta (δ), and gamma (γ). Four basic rhythms have been associated with various states:

| Rhythm | Freq (Hz) | Amp(μ V) |
|--------|-----------|---------------|
| Alpha | 8-13 | 20-200 |
| Beta | 13-30 | 5-10 |
| Delta | 1-5 | 20-200 |
| Theta | 4-8 | 10 |
| Gamma | 30-45 | 10-100 |

Table 2: EEG Frequency Bands

Alpha: The alpha wave is the most prominent rhythm in the whole realm of brain activity and possibly covers a greater range than has been previously accepted. Most subjects produce some alpha waves with their eyes closed, which is why it has been claimed that it is nothing but a waiting or scanning pattern produced by the visual regions of the brain. It is

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 5, May 2016

reduced or eliminated by opening the eyes, by hearing unfamiliar sounds, by anxiety, or mental concentration or attention. In general, the alpha rhythm is the prominent EEG wave pattern of an adult who is **awake but relaxed with eyes closed**. Alpha waves appear in the posterior half of the head and are usually found over the occipital region of the brain. They can be detected in all parts of posterior lobes of the brain. For alpha waves the frequency lies within the range of 8–13 Hz, and commonly appears as a round or sinusoidal shaped signal. However, in rare cases it may manifest itself as sharp waves. In such cases, the negative component appears to be sharp and the positive component appears to be rounded, similar to the wave morphology of the rolandic mu (μ) rhythm. An alpha wave has a higher amplitude over the occipital areas and has an amplitude of normally less than 50 μ V.

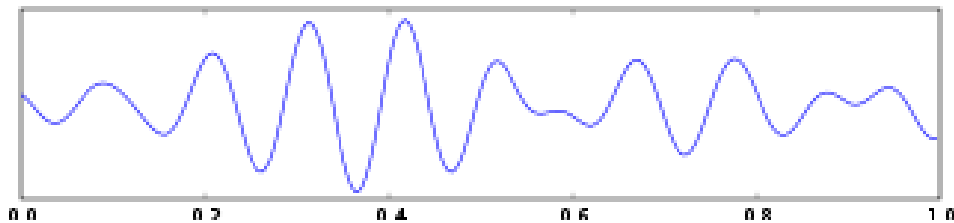


Figure 2: Alpha Signal

Beta: A beta wave is the electrical activity of the brain varying within the range of 14–26 Hz (though in some literature no upper bound is given). A beta wave is the usual waking rhythm of the brain associated with active thinking, active attention, focus on the outside world, or solving concrete problems, and is found in normal adults. A high-level beta wave may be acquired when a human is in a panic state. Rhythmical beta activity is encountered chiefly over the frontal and central regions. Amplitude of beta rhythmic normally under 30 μ V.

Beta rhythms occur in individuals who are **alert and attentive** to external stimuli or exert specific mental effort, or paradoxically, beta rhythms **also occur during deep sleep**, REM (Rapid Eye Movement) sleep when the eyes switch back and forth. This does not mean that there is less electrical activity rather that the —positivel and —negativel activities are starting to counterbalance so that the sum of the electrical activity is less. Thus, instead of getting the wave-like synchronized pattern of alpha waves, resynchronization or alpha block occurs. So, the **beta wave represents arousal of the cortex to a higher state of alertness or tension**. It may also be associated with —rememberingl or retrieving memories.

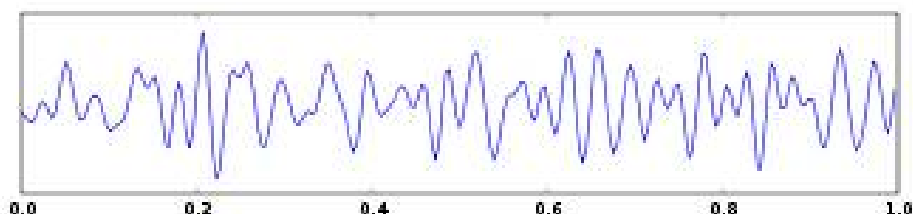


Figure 3: Beta Signal

Delta: Delta and theta rhythms are **low-frequency EEG patterns that increase during sleep in the normal adult**. As people move from lighter to deeper stages of sleep (prior to REM sleep), the occurrence of alpha waves diminish and is gradually replaced by the lower frequency theta and then delta frequency rhythms. Delta waves lie within the range of 0.5–4 Hz. These waves are primarily associated with deep sleep and may be present in the waking state. It is very easy to confuse artifact signals caused by the large muscles of the neck and jaw with the genuine delta response. This is because the muscles are near the surface of the skin and produce large signals, whereas the signal that is of interest originates from deep within the brain and is severely attenuated in passing through the skull. Nevertheless, by applying simple signal analysis methods to the EEG, it is very easy to see when the response is caused by excessive movement.

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 5, May 2016

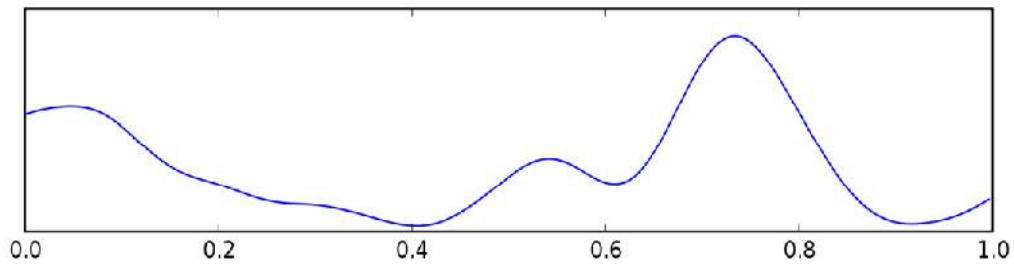


Figure 4: Delta Signal

Theta: Theta waves lie within the range of 4–7.5 Hz. The term theta might be chosen to allude to its presumed thalamic origin. Theta waves appear as consciousness slips towards drowsiness. Theta waves have been associated with access to unconscious material, creative inspiration and deep meditation. A theta wave is often accompanied by other frequencies and seems to be related to the level of arousal.

Although delta and theta rhythms are generally prominent during sleep, there are cases when delta and theta rhythms are recorded from individuals who are awake. For example, theta waves will occur for brief intervals during **emotional responses to frustrating events or situations. Delta waves may increase during difficult mental activities requiring concentration.** In general, the occurrence and amplitudes of delta and theta rhythms are highly variable within and between individuals.

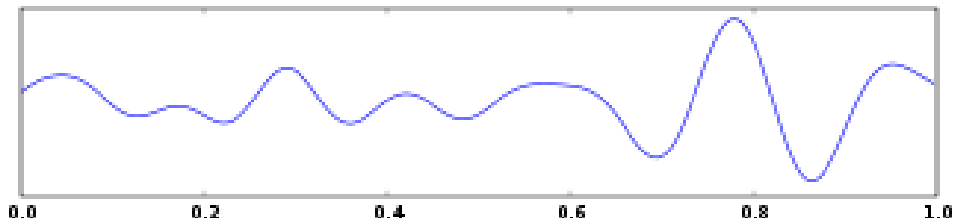


Figure 5: Theta Signal

Gamma: The frequencies above 30 Hz (mainly up to 45 Hz) correspond to the gamma range (sometimes called the fast beta wave). Although the amplitudes of these rhythms are very low and their occurrence is rare, detection of these rhythms can be used for confirmation of certain brain diseases. The regions of high EEG frequencies and highest levels of cerebral blood flow (as well as oxygen and glucose uptake) are located in the fronto-central area.

The gamma wave band has also been proved to be a good indication of event-related synchronization (ERS) of the brain and can be used to demonstrate the locus for right and left index finger movement, right toes, and the rather broad and bilateral area for tongue movement.

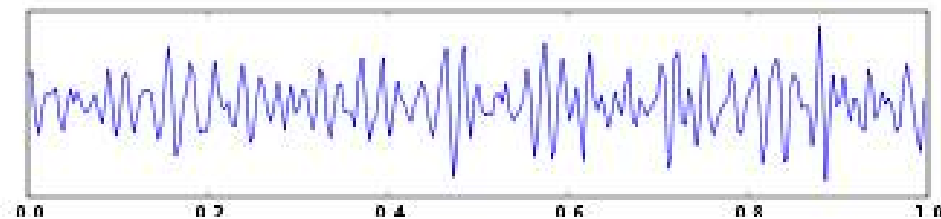


Figure 6: Gamma Signal

Several methods were proposed by different researchers to monitor the behavior of driver. Some have attempted to measure the driver's state or the vehicle's behavior to detect fatigued and drunk drivers. Meanwhile, other researchers have tried to monitor the driver, vehicle and the environment in order to detect the state of the driver. Some are discussed below

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 5, May 2016

V. SYSTEM ARCHITECTURE

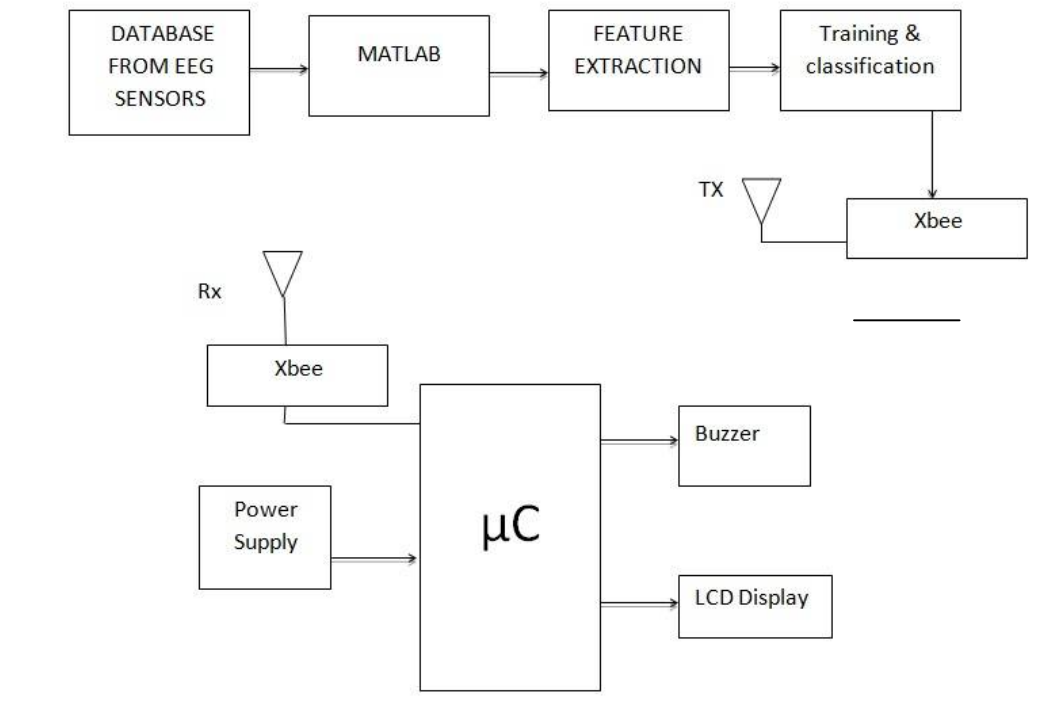


Figure 7 System Architecture

Explanation-

This block consists of the raw EEG data which are acquired from a sensor or any related perused data of EEG can be a part of this block. The data may look as follows; this is the block where the sensed data from the sensor or database is fed to. Further using MATLAB we can perform various operations to process the data in the form required by us. After the data has reached the MATLAB, we do a process called feature extraction. This process comprises of algorithms that work upon mathematically to get values of the variables needed by us. These variable values are useful in determining the characteristics of the wave shown above and hence we predict the state of the mind by just knowing these characteristics. Operations such FFT, STFT, windowing, amplitude detection are carried out here with the help of the algorithms. This part is responsible for blink detection of the eye so that it helps in detecting the drowsiness condition more accurately and thus increasing the efficiency of the system. The Xbee modules work at the 2.4 GHz frequency which means smaller board and antenna size. Xbee modules have the ability to transmit **Digital, PWM, Analog** or **Serial RS232** signals wirelessly.

SOFTWARE USED

- 1) Multisim12.0
- 2) MPLAB Pro for PIC
- 3) Proteus7.9
- 4) DipTrace

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 5, May 2016

VI. METHODOLOGY USED

Here we have cross correlation method. In this method training signal parameters are computed and stored in one array. And now we take one random signal (drowsy or Normal). And this signal will compare with training signal. And as where the maximum match is find at that place which signal is stored will be displayed.

VII. ALGORITHM USED

Firstly the training signals are made input to the system, sampled and plotted in MATLAB. Each and every signal of training signals are to be decomposed through “wavedec” function to get the Approximation and Detail coefficients with level 8. Now the last four coefficients, out of total eight coefficients of detail and approximation coefficients gives information about gamma, beta, alpha, theta and delta states of an EEG signal. Then standard mean, deviation and maximum frequency are found out of each coefficient of our interest and also plotted. These parameters are stored in an array for each signal and stored in the memory as Train_FE. Array is of 15bit each and the database for reference signals is prepared. Now a random EEG file of “.mat” format is made input to the system and same procedure of decomposition of wave and storing it is followed as done earlier for training signals with the name as FE1. Then both the Train_FE and FE1 files are loaded and each array of Train_FE is compared with FE1 array through Cross Correlation function. This gives us the best match of FE1 array from the Train_FE file, and hence the Input signal is classified as drowsy or awake signal.

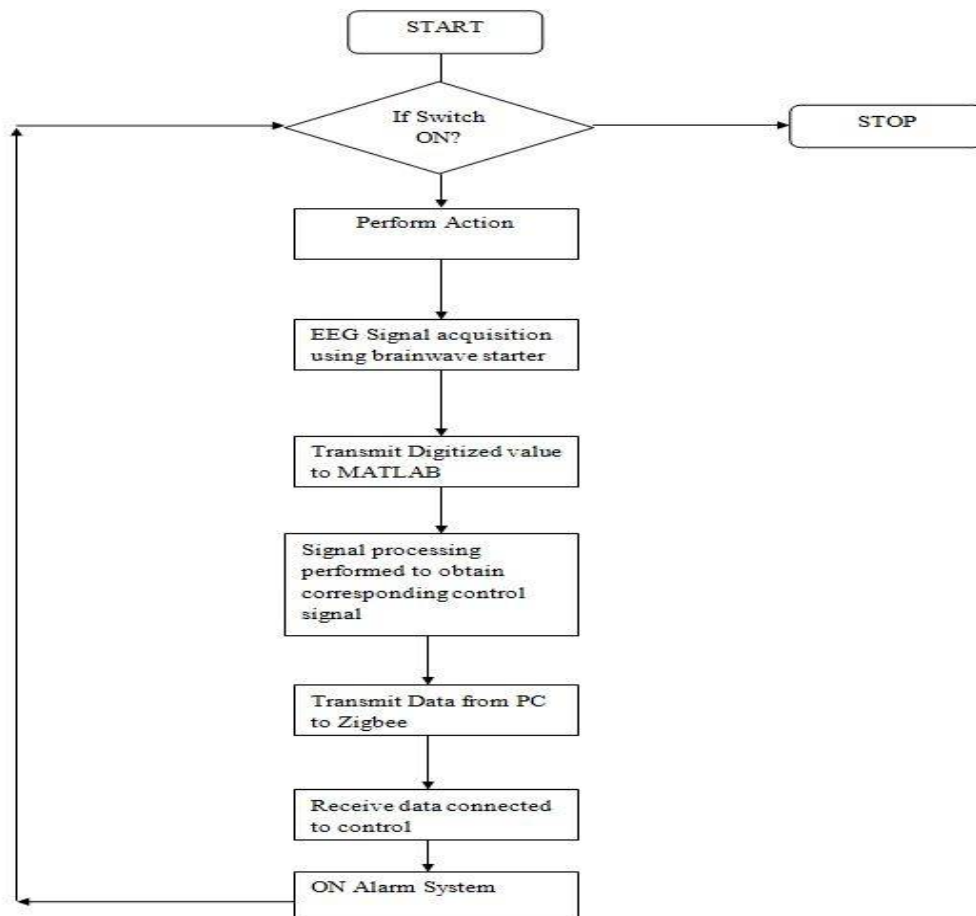


Figure 8 System Architecture Flow

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Vol. 5, Issue 5, May 2016

IX. RESULTS

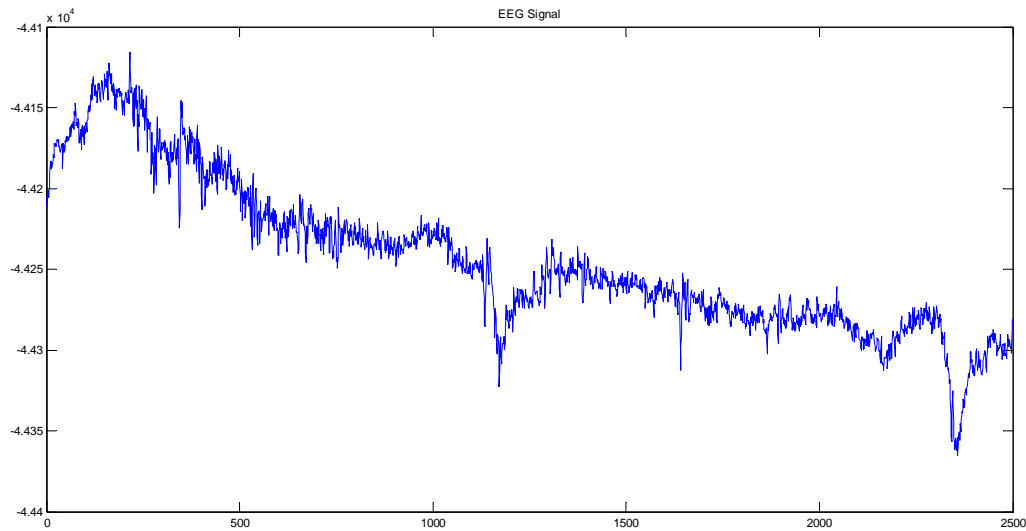


Figure 9:EEG signal contains all alpha ,beta ,theta ,delta,gamma signals with sampling frequency of 50Hz

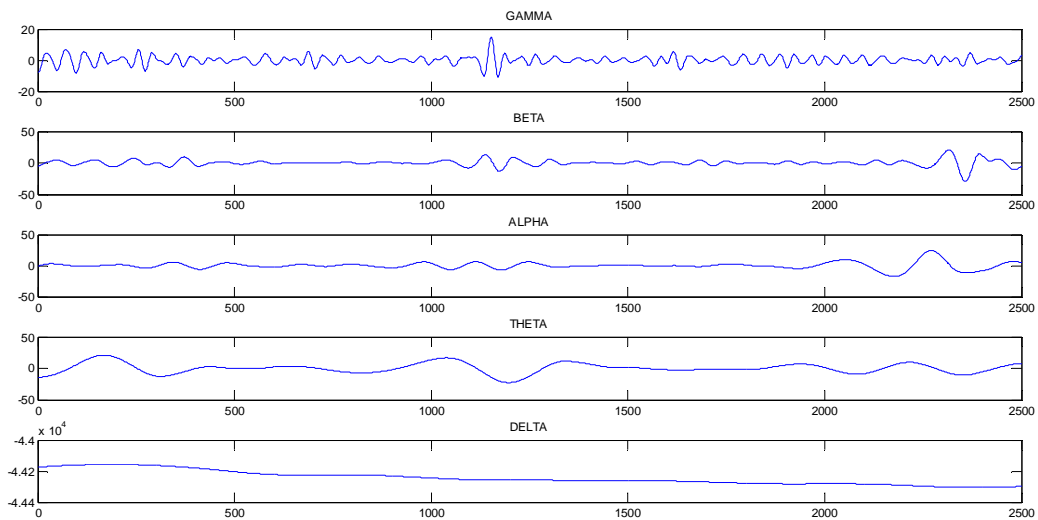


Figure10 : Decomposed EEG signal with alpha,beta,theta,delta components

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 5, May 2016

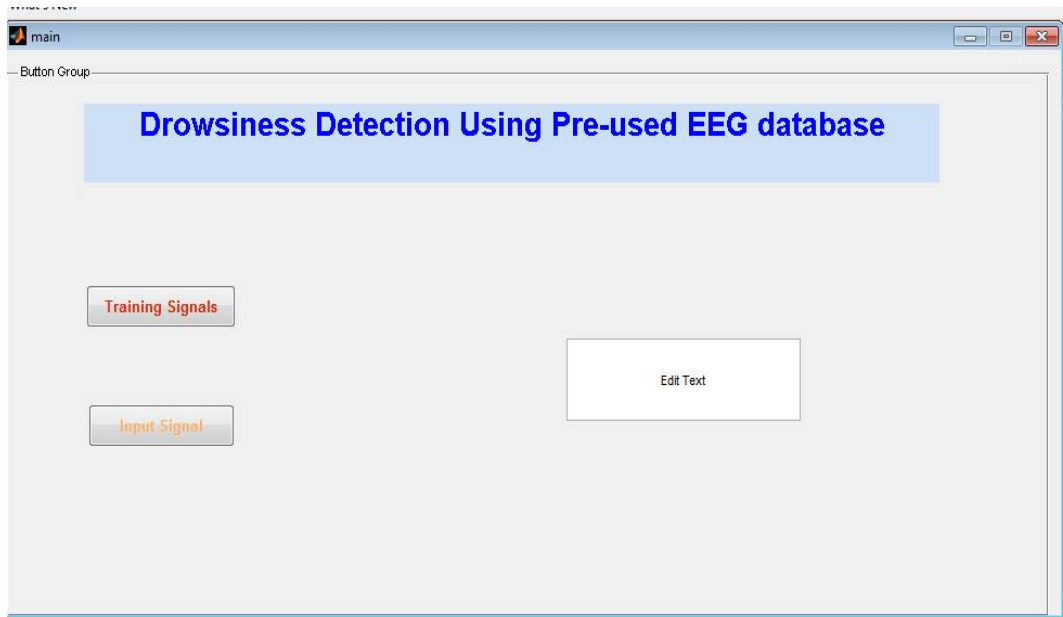


Figure 11: GUI For training and testing the EEG signal

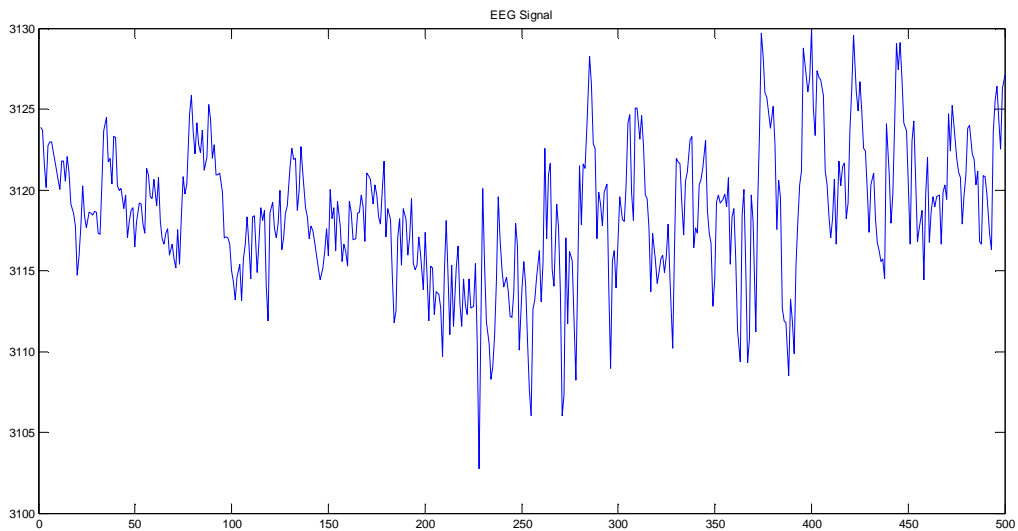


Figure 12: Standard EEG signal 1

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 5, May 2016

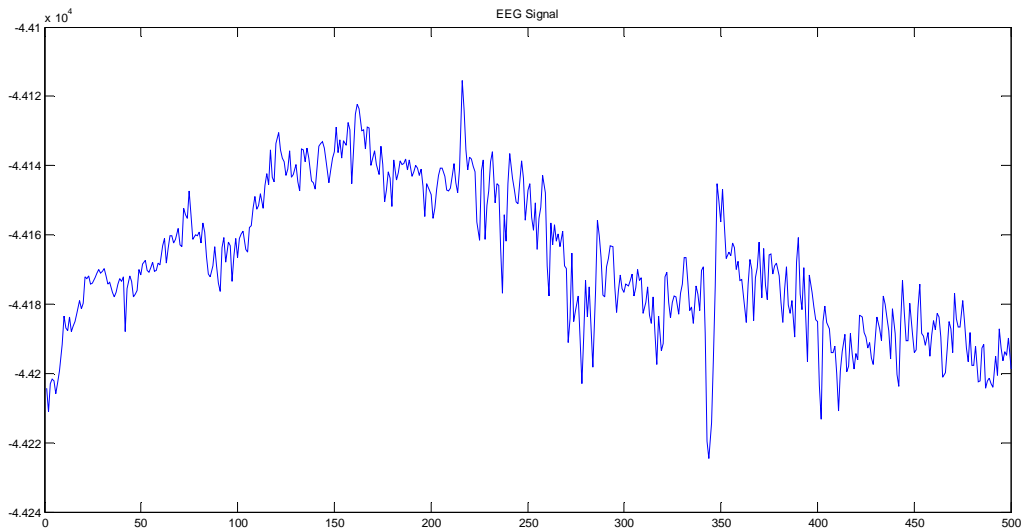


Figure 13:Standard EEG signal 2

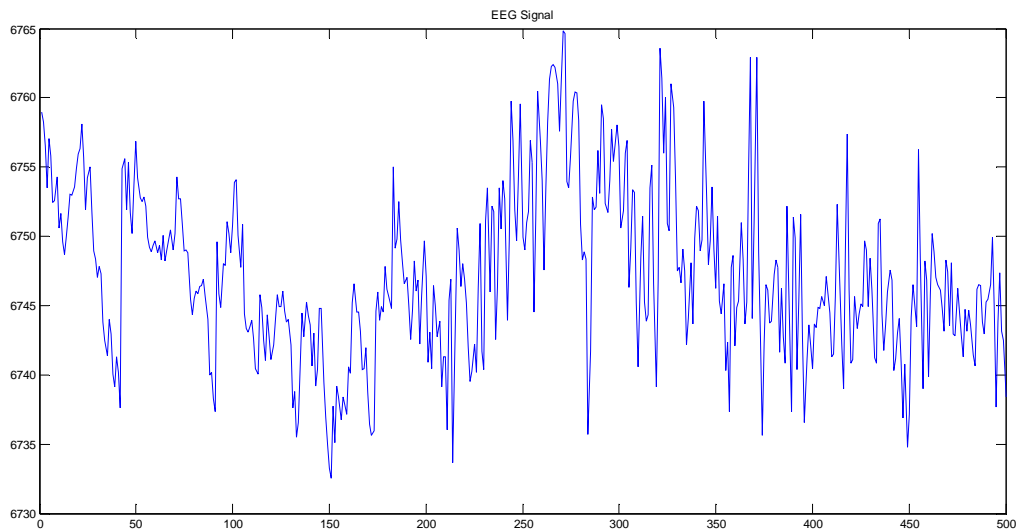


Figure 14:Standard EEG signal 3

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 5, May 2016

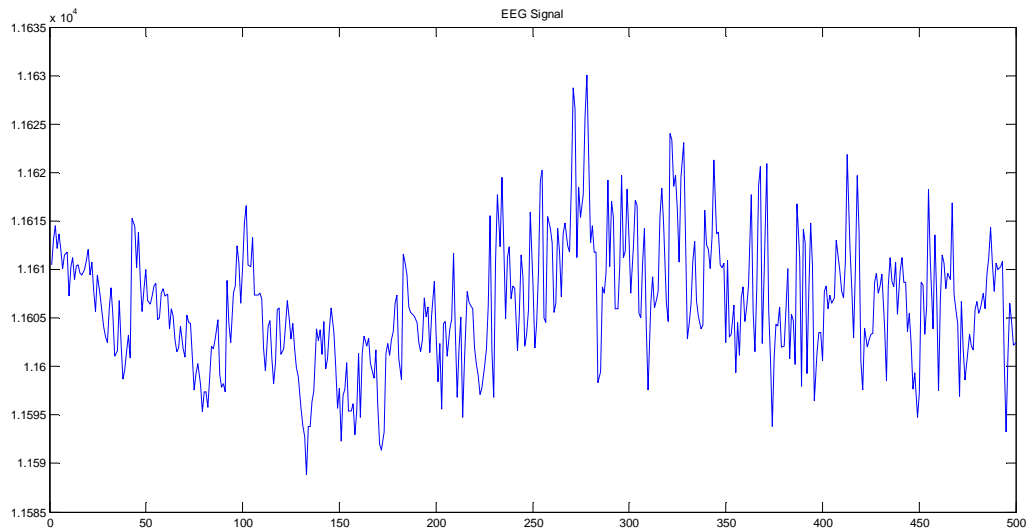


Figure 15: Standard EEG signal 4

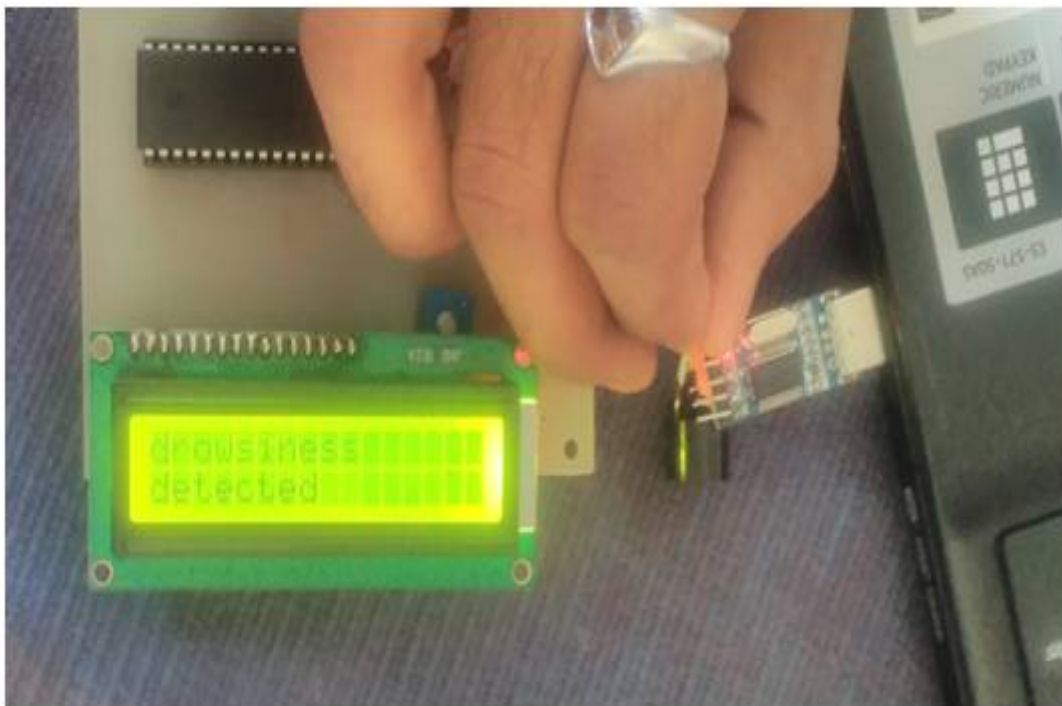


Figure 16: Drowsiness Detection

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 5, May 2016

ADVANTAGES

1. By using EEG signals we can predefined the drivers condition by analyzing the sensor outputs i.e from alpha and beta ranges and from that we can have our further system for the accident prevention due to driver's drowsiness
2. Our system can also be used in various workplace for determining conditions of workers through EEG sensors and so that we can take further remedy actions

APPLICATIONS

1. Cars, Locomotives and other vehicles to avoid accidents
2. Can be implemented at extreme work places to avoid fatal accidents
3. Can be used in the field of stress management

X. CONCLUSION

In this project we have cross-correlation algorithm for finding the input signal is either drowsy or awake signal. First we have created training datasets from standard EEG and awake signals and we compute standard deviation, mean and maximum frequency of that signals and all these features stored in one array. Now as we give input signal it will compare with all the above training signals and where maximum match is found then corresponding that state is detected as drowsy state is detected signal send through Zigbee to microcontroller and buzzer will turn on. So we can alert driver which is driving. We can use actual sensors for taking real time signals and performing drowsy state or awake state. We can implement vehicle to vehicle communication for alerting the vehicles coming from front side. We can use Raspberry Pi, DSP processor as a replacement of laptop or desktop where our model can become actual product. Artifact detection also includes in this part to achieve high accuracy.

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