World Applied Sciences Journal 27 (2): 148-154, 2013
ISSN 1818-4952

DOI: 10.5829/idosi.wasj.2013.27.02.1542

Vigilance Estimation Using Brain Machine Interface

[1]Najdah Mehar, [1]Sana Zamir, [1]Alina Zulfiqar,
[1]Sheerjeel Farouqui, Abdur Rehman and [2]Maj. Adnan Rashdi

[1]Foundation University Rawalpindi Campus, Pakistan
[2]Military College of Signals (MCS) NUST, Pakistan

Abstract: A vigilance estimation system capable of detecting drowsiness based on brain signals 'electroencephalogram signals' analysis has been developed. The system uses single channel passive electrodes module to acquire electroencephalogram signals. The algorithm then analyzes electroencephalogram signals to determine state of mental alertness 'vigilance'. In case of drowsiness the system generates an alarm to alert the user which may be an aircraft pilot or a car driver. This design project implements a means comparison test (MCT) to detect changes in alpha relative power band (8-12Hz) which is an indicator for drowsiness in electroencephalogram signals analysis. In our project detection threshold do not require tuning parameters as it is independent of the subject. The system can distinguish alertness and drowsiness in real-time. Analysis is conducted on different subjects to verify the accuracy of the prototype.

Key words: EEG electroencephalogram · MCT Means Comparison Test · EOG electro-oculogram · ECG electrocardiogram · AP action potential · P3 parietal · O1 occipital · STFT short time Fourier transform · BMI Brain Machine Interface.

INTRODUCTION

Main Reasons for Any Accidents Are Related To:

- Man
- Machine
- Media

The safety organizations have evaluated that 90% of the accidents occur due to 'man'. If we further sub divide the cause of 'man' its leads to

- Unsafe acts
- Competence level
- Medical incapacitation
- Natural Limits

Low Vigilance or mental alertness is one of the causes of accidents. Inadequate rest or monotonous media leads to drowsiness during driving or flying and may leads to accident. Various studies have shown that 10 to 25 percent of severe traffic accidents can be attributes to drowsiness. In medical terms drowsiness is the transitional state between sleep and awake. During drowsiness, vigilance is obscured and reduces the alertness level. This is considered to be a serious cause of accidents, specially the tasks that needs sustained and good attention level Roads and high ways are the main means of communication. In spite of best safety practices, almost 1.2 million people die in the road accidents and a 50 million are injured. (http://hubpages.com/hub/Texas-Automobile-Accident).

Safety of human life is paramount. More over financial losses due to unsafe acts or accidents are considered to be avoidable. Vigilance estimation system is likely to help the elimination of one of the causes 'drowsiness'

This system leads to sensor development, Signal processing and there after interpretation for evaluating the alertness level of the sample. Robustness, price and automotive constraints need to be realistic as well.

In this Paper we aim to propose a real- time method for detecting decline in driver's alertness. EEG signals initiated by the brain of the subject will be captured by the four channel accident avoidance system. The recordings include four main EEG channels, (F3) Left Frontal, (C3) central, (P3) parietal and (O1) occipital.

Corresponding Author: Najdah Mehar, Foundation University Rawalpindi Campus, Pakistan.

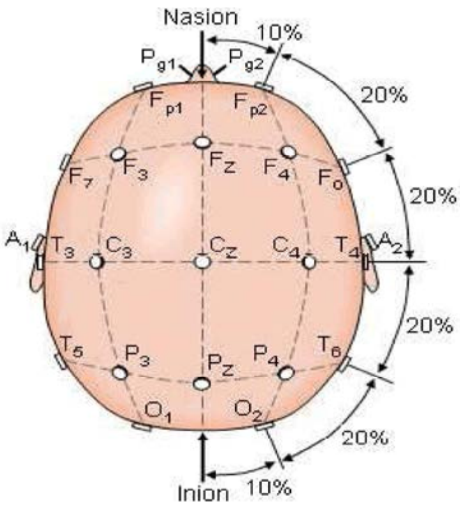

Fig. 1: Electrode placement positions for EEG measurement (Antoine Picot, Sylvie Charbonnier and Alice Caplier, 2008)

Fig. 2: The experimental environment(Mu-Chun Su, Senior Member, IEEE, Chao-Yueh Hsiung, and De-Yuan Huang,2006

Background: The monitoring of drivers state can be classified:

- Man, the driver's physical behavior

The driver's physiological behavior

- Machine, Vehicle

The physical behavior of the driver while driving could be high alertness, low alertness, very low alertness, no alert. Very low alert is the situation of drowsiness. Face, mouth and eyes are the primary indicators of drowsiness. Eye blinking or yawning can be tracked by tracking algorithms, which detect the frequency and duration of eye blinking and yawning. High frequency is indicative of decreased attention. Stereoscopic camera can be used for calculating the gaze. However fatigue monitoring is difficult using these features.

Video features are the best indicators of drowsiness. More over physiological indicators are considered to be the best indicators.

EEG is considered to be a useful and promising indicator of drowsiness so we will be focusing on this technique in our paper.

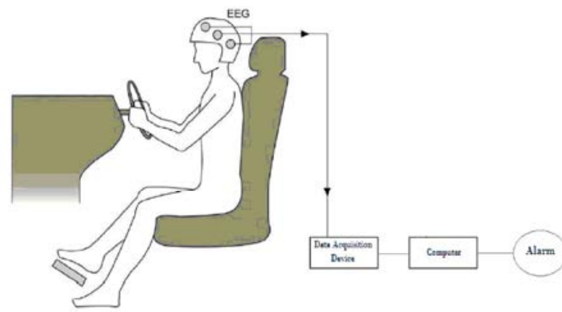

Fig. 3: Systematic implementation of Drowsiness Estimation System.

Behavior of Brain waves

Table 1: Frequency of Brain Waves

Type	Frequency (Hz)	Behavior
Delta	up to 4	• Slow wave sleep in adults, and some continuous attention tasks.
Theta	4 – 7 Hz	• Drowsiness or arousal in older children and adults, idling.
Alpha	8 – 12 Hz	• Relaxed/reflecting, closing the eyes.
Beta	12 – 30 Hz	• Alert/working, active, busy or anxious thinking, active concentration.
Gamma	30 – 100 +	• Perception which combines two different senses, such as sound and sight and short term memory matching of recognized objects, sounds, or tactile sensations.

Research Strategy

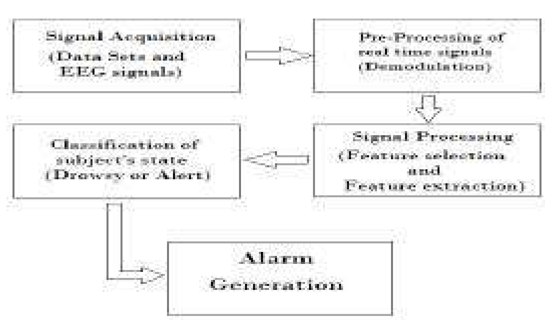

Fig. 4: The EEG automated sleep stage detection process

Flow Chart of the Analysis

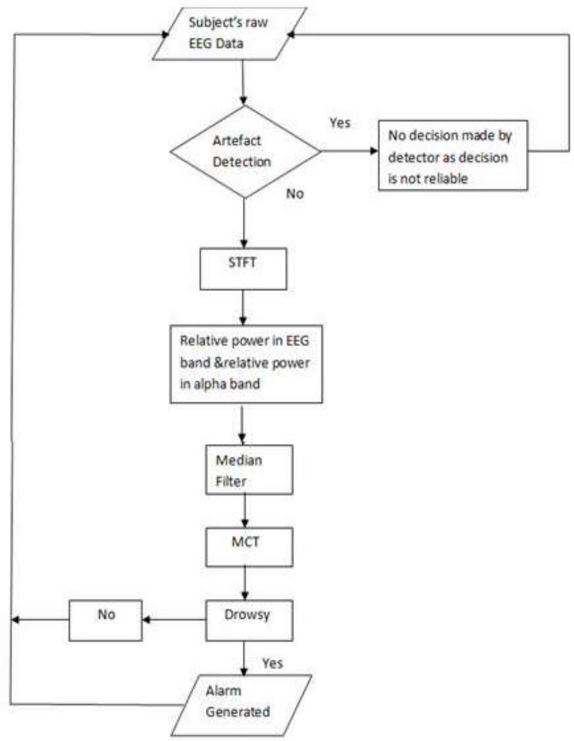

Fig. 5: Summary of the EEG processing algorithm

Power Spectrum Computation Using Short Time Fourier Transform: Short Time Fourier Transform is used to compute EEG power spectrum. On a window of two seconds, every second power spectrum is computed using Welch's periodogram method. Overlapping window of one second is used. The relative powers in each band are computed every second as the ratio of the power in alpha band and the power of whole EEG spectrum (Antoine Picot, Sylvie Charbonnier and Alice Caplier, 2008)

$$\alpha_{relative-power} = \frac{\alpha_{power}}{EEG_{power}} \quad (1)$$

Short Time Fourier Transform: In case of real time signals or non-stationary signals, instead of Fourier transform short Fourier transform is used as Fourier transform lacks behind in providing any information regarding time. One solution to this problem is short time Fourier transform which can provide information regarding time resolution. STFT takes Fourier transform of segmented consecutive pieces of a signal and then each Fourier transform then provides the spectral content of that time segment only.

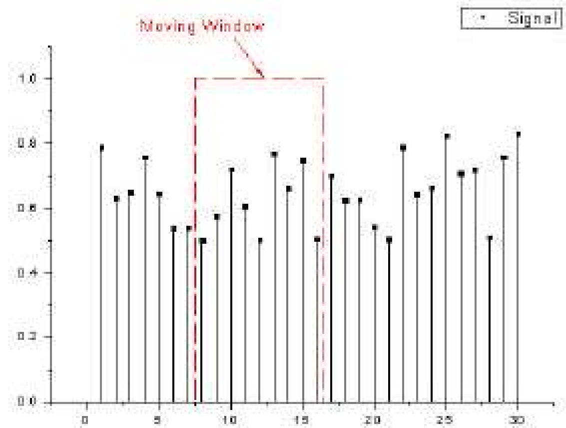

Fig. 6: Short time Fourier Transform Windowing Concept

For analyzing non-stationary signals, a signal processing method called Short –Time Fourier Transform is used. A window that moves with respect to time analyzes several frames of the signals which are extracted by STFT. Sufficiently narrowing the time window will lead to each frame extracted as stationary. Doing so, Fourier Transform can be used. The relation between the variance of frequency and time can be identified with the help of window moving along the time axis.

Welch's Periodogram Method: The power spectral density of the input signal is estimated through Welch's periodogram method. Overlapping of segments, computation of the periodogram of the over lapping segments, averaging of the resulting periodogram to produce the power spectral density estimate is all done by using Welch's method. The estimation of the power of a signal vs. frequency is done by Welch's method.

The concept of using periodogram spectrum estimates is the basis of Welch's Method. The reduction of noise in the estimated power spectra in exchange for reducing the frequency resolution can also be done using Welch's method.

The Method Is Based on Following Concept: The signal is split up into overlapping segments: The original data segment is split up into L data segments of length M, overlapping by D points.

- If D = M / 2, the overlap is said to be 50%
- If D = 0, the overlap is said to be 0%.
- The overlapping segments are then windowed: After the data is split up into overlapping segments, the individual L data segments have a window applied to them (in the time domain).

After performing the above mentioned steps, The discrete Fourier transform is used to calculate the periodogram. The squared magnitude of the result is also computed. In order to reduce the variances of the individual power measurements, the individual periodogram are then time averaged. Resultant will be an array of power measurements vs. frequency.

Median Filtering: It is often desirable, in processing of signal to perform some kind of noise reduction on signal or an image. To remove noise median filter is used as it is a non- linear digital filtering technique. This technique replaces the center value in the window with the median value of all points within the window.

Median filtering is a digital filtering technique, used to reject abnormal values and remove noise. Median filtering will smooth the alpha relative signal using a sliding window of 10 seconds. In order to implement one-dimensional median filtering MATLAB command 'medfilt1' is used, which is a non-linear technique that applies sliding window to the sequence. One window of 10 seconds will include 1000 samples.

Means Comparison Test: In order to compare two populations, statistical parameters are often desired. statistical inference for one population parameter, confidence intervals and tests of significance are useful statistical tools for the difference between two population parameters.

Means comparison test is computed to compare the alpha relative powers in reference window and moving window. The reference window is calculated at the beginning of recording, assuming that driver in alert stage. Mean value calculated at this stage will give reference mean value denoted by $\overline{X}_1$ and the mean calculated for the moving window is $\overline{X}_2$. n_1 and n_2 represent lengths of fixed and moving window respectively. s_1 and s_2 are the variances. Threshold value will then classify the stage of drowsy or alert. The decision threshold value used is 3, which is an empirically chosen value and is mentioned in an IEEE research paper (inspired by Antonie Picot). Hence the formula used is (Antoine Picot, Sylvie Charbonnier and Alice Caplier, 2008)

$$u=\frac{\overline{X}_1-\overline{X}_2}{\sqrt{\frac{s_1^2}{n_1}+\frac{s_2^2}{n_2}}} \qquad (2)$$

Window No	Software Result W/D	Known Result W/D	Classification
Window 1	W	W	1
Window 2	W	D	0
⋮	⋮	⋮	⋮

Fig. 7: Matrices Concept for Verification Block

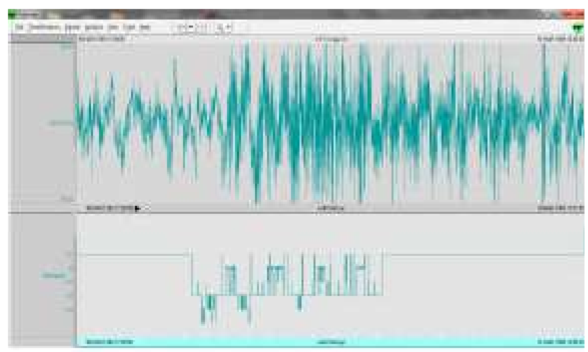

Fig. 8: 24 Hours EEG signal recording in Polyman

Classification: A verification block has been implemented in order to find out the accuracy of classified results. To implement this block we used the concept of matrices.

We tested our algorithm accuracy using wake stage data and then sleep stage data. Third column, which is classification column, indicates correct or false detection of states by the implemented algorithm. 1 represents correct classification and 0 represents false detection. This means that using wake stage data only if algorithm classified 'Drowsy' then it is false detection and marked as 0 but in case of 'Wake detection 1 is marked as it is correct classification. For each window same procedure is repeated and a percentage is finally calculated which verifies accuracy of implemented algorithm.

In a 24 hour recording which was acquired from 'Physionet' website the stage of alert and sleep can be clearly distinguished using software called 'Polyman'. This software can support 'EDF' format and can clearly identify the transition state. Below figure is an illustration of a 24 hour recording in EDF format in polyman software. It is a time domain display in which there are two panes. The pane above is an active time domain display of EEG signal and the pane below is hypnogram of the the EEG signal. Hypnogram is a brain signal graph that can show the various transition states. Among which 'W' is wake state and 'N1' is sleep state.

RESULTS

This algorithm was tested on the datasets acquired from 'Physionet' website. Datasets are 24 hours EEG recording representing both alert and drowsy states. Using implemented algorithm accuracy of correct detection achieved was 79.22% and 20.78% was the false detection accuracy.

Drowsiness Detection Real-Time Algorithm: Drowsiness detection algorithm was initially implemented on the datasets for the purpose of off-line analysis and accuracy achieved for correct detection was 79.22%. The next step was to modify the code for real-time analysis. For this, we added three new blocks. These are:

- Signal acquisition from hardware
- Demodulation
- Low pass filter

Signal Acquisition: First, EEG signals (brain signals) were acquired from the hardware device. Then using built-in soundcard of computer these signals were imported to MATLAB workspace using command 'analoginput'. An object 'ai' was created for the soundcard having hardware device adapter name 'winsound'. Hardware channels are not present when an analog input object is created. For execution of the device object, hardware channels are added. The sample rate is set to 44.1 kHz and samples per trigger could vary according to the duration set. The relationship to set the duration is:

$$\text{Duration}=\frac{\text{Samples PerTrigger}}{\text{Sample Rate}} \tag{3}$$

This duration will determine for how long EEG signals will be recorded. In order to process the most recently acquired analog data, a non-blocking control command 'peekdata' was used. For a real-time display 'drawnow' command was used, which can update the plot and provide a display of most recently acquired samples.

Demodulation: Modulated EEG signals were acquired from the single channel acquisition device. In order to recover the baseband signal i.e EEG signal, envelope detection technique was used. This brain signal can be further processed in order to classify the stage of alertness or drowsy. Envelope detection technique is implemented by using Hilbert transform and then computing its magnitude in order to generate signal envelope. Modulation index can be computed using following equation:

$$M=\frac{(\text{Maxium-Minimum})}{(\text{Maxium+Minimum})} \tag{4}$$

A script function is defined which can be further called in the file implementing drowsiness detection algorithm and thereby demodulating incoming modulated EEG signal.

Filtering: A low pass filter having a cut-off frequency of 50 Hz and attenuation -40dB was designed in MATLAB fdatool. Attenuation of -40dB means that for an input signal of 100volts output would be attenuated by a factor of 0.0001volts, thereby giving an output of 0.01volts. This filter will allow low frequencies to pass while blocking higher frequencies. A band pass filter was also designed in MATLAB fdatool having cut-off value of 8 to 12 Hz. This filter allows alpha band to pass while blocks other frequencies.

Off-Line Algorithm Adaption for Real-Time Analysis: The algorithm which was implemented for off-line analysis is slightly modified for real-time analysis. These modifications include sampling rate which is now 44100 samples per second instead of 100 samples per second. Power spectrum is computed every second on a window of two seconds with an overlapping window of one second. Median filtering and means comparison test parameters remain the same For median filter, one window of 10 seconds will now include 441000 samples. The algorithm can now work on-line. However, sliding window of 10 seconds used for median filtering introduces a delay of 6 seconds and 30 seconds sliding window used for MCT introduces a delay of 16 seconds, therefore the decision is made by real-time algorithm every 22 seconds.

Low Pass Filter and Demodulated Signal: The figure shown below is a time vs. amplitude plot. It represents a time domain real-time signal. EEG signals were recorded for 10 seconds when the subject was in alert state.

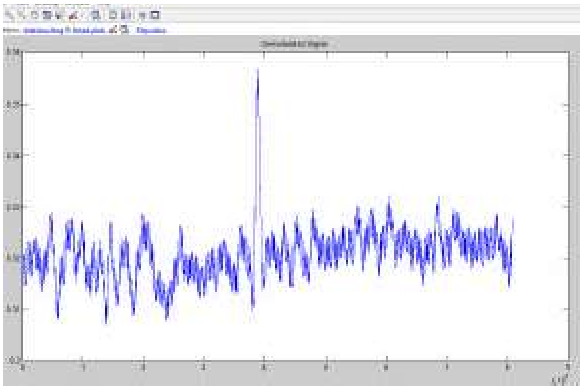

Fig. 9: Recovered EEG signal

This recording includes a total number of 441000 samples. This EEG signal has amplitude of 10uVolts to 100uVolts and frequency range of 0.5 to 40Hz.

RESULTS AND ANALYSIS

The real-time drowsiness detection algorithm was tested on four subjects of different ages, among which 3 were female subjects of ages 23, 20 and 22 whereas, 1 was a male subject of age 54 years. EEG signals were recorded for duration of half an hour, 1 hour and 3 hours. The percentage of correct detection came out to be 87.16% and false detection percentage is 12.84% for a detection threshold value of 3.

The Figures 12, 13, 14 and 15 are time vs. amplitude plots and represent how EEG signals are processed using drowsiness detection algorithm. First EEG signals are recorded Figure 38, then relative power in alpha band is computed Figure 39, median filtering is then used to smooth the signal Figure 40 and finally after performing MCT decision is made on basis of threshold value Figure 41. The results shown in these figures are of a 23 years old female subject and recordings were taken for 3 hours and consist of 476,280,000 samples. Figures are time vs. amplitude plots.

Different EEG Signals: In order to study the changes in EEG signal waveforms, recordings were taken when subject was sleeping, when subject was alert but focusing on some complex mathematical computation and also when subject was relaxed but alert. Recordings were taken for half an hour and consist of 79,380,000 samples. Figures 16, 17, 18 are time vs. amplitude plots.

Applications:

- Pilot

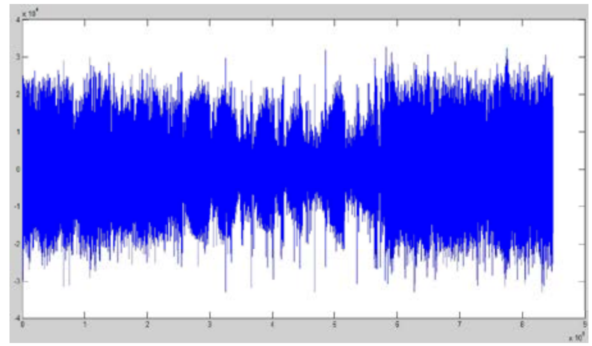

Fig. 10: Real-Time EEG Signal

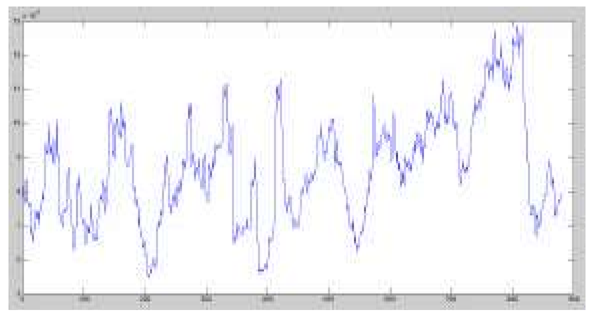

Fig. 11: Relative Power in Alpha Band

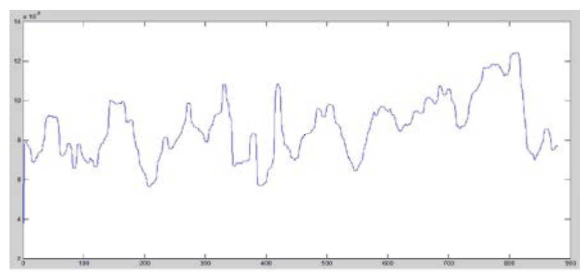

Fig. 12: Smoothed by Median Filter

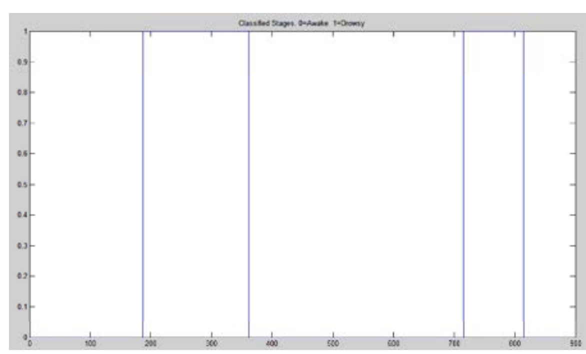

Fig. 13: Classification of Alert or Drowsy State on basis of Detection Threshold

- Train driver
- Car driver

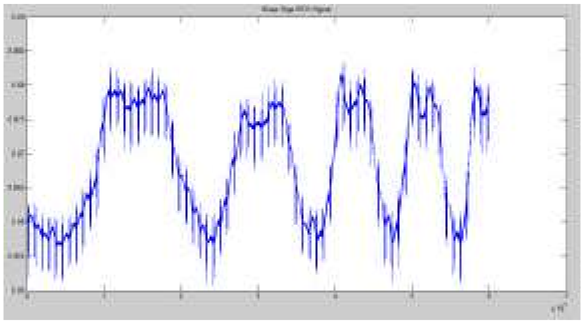
Fig. 16: Sleep Stage EEG Signals

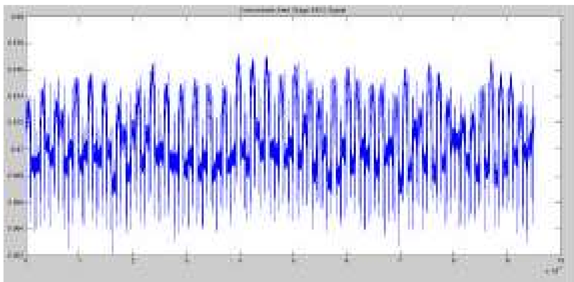
Fig. 17: Alert Sate EEG Signals in Concentration Mode

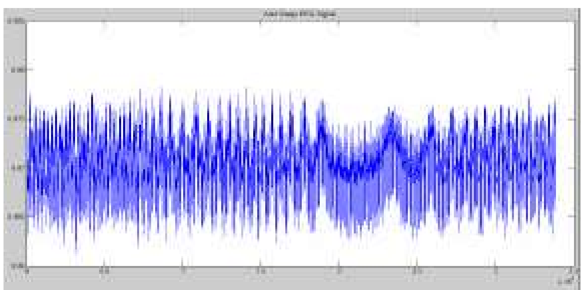
Fig. 18: Alert State EEG Signals in Relaxed Mode

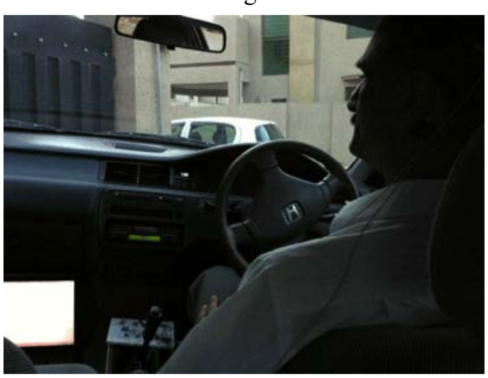
Fig. 19: Driver using vigilance estimation system

All the drivers mentioned above travel for long distances and hence they suffer from cognitive states. So the proposed design is very much applicable in order to avoid traffic accidents.

- Driving Related Applications

Elimination of fatigue/drowsiness related car accidents

- 1,500 less highway fatalities per year.
- 71,000 less motor-vehicle related injuries per year.
- $12.5 billion saved per year.

Provide late night drivers with a sense of safety.

- Medical/Everyday Applications

- Keep hospital patients with concussions awake.
- Avoid nodding off at work.
- Stay awake in class.

CONCLUSION

This paper is an implementation of a driver drowsiness estimation system based on EEG. A system will be developed to acquire EEG signals. After analysis and processing on these signals an alarm will be generated when the subject feels drowsy. This alarm will alert the subject in order to avoid any hazardous situation.

REFERENCES

1. Antoine Picot, Sylvie Charbonnier and Alice Caplier, “On-Line Automatic Detection of Driver Drowsiness Using a Single Electroencephalographic Channel”, 30th Annual International IEEE EMBS Conference Vancouver, British Columbia, Canada, August 20-24, 2008.
2. Chambers, J.A. and saeid sanei EEG signal processing
3. Mu-Chun Su, Senior Member, IEEE, Chao-Yueh Hsiung and De-Yuan Huang,” A Simple Approach to Implementing a System for Monitoring Driver Inattention”, 2006 IEEE International Conference on Systems, Man and Cybernetics October 8-11, 2006, Taipei, Taiwan
4. http://hubpages.com/hub/Texas-Automobile-Accident.