Design Approach For EEG-Based Human Computer Interaction Driver Monitoring System

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Design Approach For EEG-Based Human Computer Interaction Driver Monitoring System

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Abstract- According to a 2012 poll conducted by the National Sleep Foundation, one in five pilots admit that they have made a serious error, and one in six train operators and truck drivers say that they have had a “near miss” due to sleepiness. It has been observed that the road accidents are caused not only because of driver’s physical fatigue but also due to driver’s mental fatigue. Driving is a complex task, requiring full concentration and a calm attitude. Stressed and strong emotions, whether they result from the driving task itself or unrelated matters, can affect a driver’s abilities. There is always a need for a system that will continuously monitor the driver’s physical and mental state. Researchers have used a technique called electroencephalography (EEG) to analyze the drivers' brain signals. This paper investigates the recent research going on in the development of EEG-based Driver Assistant/Monitoring System. Also we have given a brief description of the proposed driver monitoring system.

Keywords – Brain Machine Interface (BMI), Brain Computer Interface (BCI), Human Computer Interaction (HCI), Electroencephalogram (EEG), driver assistance

I. INTRODUCTION

Driving is a complex task, requiring full concentration and a calm attitude. Stressed and strong emotions, whether they result from the driving task itself or unrelated matters, can affect a driver’s abilities. For example, research has shown that angry drivers are more likely to take risks such as speeding, rapidly switching lanes, tailgating and jumping red lights. EEG signal can be one of the features of BCI for detecting driver’s state of mind.

The main objective of this paper is to study the different mental state recognition methods based on EEG signals. Later work can be done on analyzing different mental states of a driver in different traffic situation and based on the study, predicting whether driver is mentally fit or not. In recent past, it has been observed that drivers with mental fatigue lead to accident. In [1], authors have proposed a robust real-time embedded platform to monitor the loss of attention of the driver during day and night driving conditions. The alertness level can be assessed using different measures [2], such as electroencephalogram (EEG) signals [3], ocular features [4], blood samples [4], speech [5], [6], and others. The EEG-based method has been reported to be highly authentic for estimating the state of drowsiness [3]. In [7], a novel method for multifractal analysis of EEG signals named generalized Higuchi fractal dimension spectrum (GHFDS) was proposed and applied in mental arithmetic task recognition from EEG signals.

II. EEG BASED EMOTION RECOGNITION

Many methods for estimating human emotion have been proposed in the past. The conventional methods basically utilize audio and visual attributes to model human emotional responses, such as speech, facial expressions, and body gestures. More recently, accessing physiological responses has gained increasing attention in characterizing the emotional states [8]–[11].

In addition to periphery biosignals, signals captured from the brain in central nervous system (CNS) have been proved to provide informative characteristics in responses to the emotional states. The ongoing brain activity recorded using EEG provides noninvasive measurement with temporal resolution in milliseconds. EEG has been used in cognitive neuroscience to investigate the regulation and processing of emotion for the past decades. Power spectra of the EEG were often assessed in several distinct frequency bands, such as delta (δ: 1–3 Hz), theta (θ:4–7 Hz), alpha (α:

8–13 Hz), beta (β: 14–30 Hz), and gamma (γ: 31–50 Hz) , to examine their relationship with the emotional states. Among the EEG-based emotion recognition works which implemented experiments using audio stimuli to collect EEG data, there are some works where subjects' emotions were elicited by pre-labeled music with emotions.

There are an increasing number of researches done on EEG-based emotion recognition algorithms. In [12], short-time Fourier Transform was used to calculate the power difference between 12 symmetric electrodes pairs with 6 different EEG waves for feature extraction and Support Vector Machine (SVM) approach was employed to classify the data into different emotion modes. The result was 90.72% accuracy to distinguish the feelings of joy, sadness, anger and pleasure. A performance rate of 92.3% was obtained in [13] using Binary Linear Fisher's Discriminant Analysis and emotion states among positive/arousal, positive/calm, negative/calm and negative/arousal were differentiated. SVM was applied in [14] for emotion classification with the accuracy for valence and arousal identification as 32% and 37% respectively. By applying lifting based wavelet transforms to extract features and Fuzzy C-Means clustering to do classification, sadness, happiness, disgust, and fear were recognized in [15]. In [16], optimization such as different window sizes, band-pass filters, normalization approaches and dimensionality reduction methods were investigated, and it achieved an increase in accuracy from 36.3% to 62.07% by SVM after applying these optimizations. Three emotion states: pleasant, neutral, and unpleasant were distinguished. By using Relevant Vector Machine, differentiation between happy and relaxed, relaxed and sad, happy and sad with a performance rate around 90% was obtained in [17].

In another work [18], author has classified distraction level of driver using EEG signals. The driver distraction has been classified into four levels neutral, low, medium and high. The analysis of variance (ANOVA) was performed. Two different features namely: spectral centroid (SC) and power spectral density (PSD) has been derived from the recorded EEG signals. The fuzzy classifier is used to classify the distraction levels. The highest classification rate of 91.99% was obtained in determining low level of distraction. The overall classification accuracy was 79.21%. The work suggested that EEG signals can be used to monitor distraction level intensity in order to alert drivers to high levels of distraction.

III. Steady state visual evoked potential (SSVEP)

In neurology, Steady State Visually Evoked Potentials (SSVEP) are signals that are natural responses to visual stimulation at specific frequencies. When the retina is excited by a visual stimulus ranging from 3.5 Hz to 75 Hz, the brain generates electrical activity at the same (or multiples of) frequency of the visual stimulus. Recently, SSVEPs found a novel application for SSVEP-driven brain-computer interface (BCI) systems.

The steady-state visual evoked potential is a kind of EEG, which is widely used. When our eyes are stimulated by a transient flash, transient VEP, as the respond to this stimulus, can be recorded on the scalp. When the flash stimulus repetition rate is fast enough, for example, the stimulus interval is less than 125ms or stimulus frequency is higher than 8Hz, and the scanning time is a few times as long as the stimulus intervals, we can record the steady state VEP. Its amplitude varies with the stimulus frequency, stimulus intensity, stimulus size and many other factors [19]. When the flash illumination stimulation changes in a form of a sine wave, the amplitude of SSVEP increases linearly to the maximum along with the increasing depth of sinusoidal, then it is saturated. The critical frequency which makes transient VEP change to steady-state VEP is different when stimulation patterns are different. Specifically, the sine wave stimulation requires stimulation frequency above 4Hz, and the rectangular wave stimulation need more higher frequency, usually 8-10Hz [20].

The steady-state VEP can be recorded in the occipital region called the steady-state visual evoked potential. Using SSVEP and Linear discriminant analysis (LDA) using three types of EEG characteristics showed that the mean recognition accuracy was 66.3% [20]. Compared to other modalities for brain computer interface (BCI) applications, such as the P300-based and the slow cortical response-based BCIs, an SSVEP-based BCI system has the advantage of better accuracy, higher information transfer rate (ITR) and short/no training time. However, similar to other BCI modalities, most current SSVEP-based BCI techniques also face some challenges that prevent them from being accepted by the majority of the population.

IV. Related Work

German researchers have used drivers' brain signals, for the first time, to assist in braking, providing much quicker reaction times and a potential solution to the thousands of car accidents that are caused by human error. Using electroencephalography (EEG) - a technique that attaches electrodes to the scalp, the researchers demonstrated that the mind-reading system, accompanied with modern traffic sensors, could detect a driver's intention to break 130 milliseconds faster than a normal brake pedal response [21]. Driving at 100km/h, this amounts to reducing the braking distance by 3.66 meters -the full length of a compact car or the potential margin between causing and avoiding accidents. The study identified the parts of the brain that are most active when braking and used a driving simulator to demonstrate the viability of mind-reading assisted driving. As well as EEG, the researchers, from the Berlin Institute for Technology, also chose to examine myoelectric (EMG) activity which is caused by muscle tension in the lower leg and can be used to detect leg motion before it actually moves to the brake pedal.

Whilst sat among conventional driving controls, the study's 18 participants were asked to drive a car that was displayed on a screen in front of them whilst a series of electrodes were attached to their scalp to measure brain activity. They were asked to stay within a 20 metre distance of a computer-controlled lead vehicle along a road that contained sharp curves and dense oncoming traffic, to recreate real driving conditions, whilst maintaining a speed of 100km/h. At random intervals, emergency braking situations were triggered by the rapid braking of the lead vehicle in front, accompanied by the flashing of its braking lights. At this point, when the subjects reacted, the data was collected from the EEG and EMG. For comparison, the researchers also recorded information on the time it took to release the gas pedal and press the brake pedal, the deceleration of both vehicles and the distance between the two vehicles.

Using the initial EEG recordings, the researchers were able to determine what parts of the brain are most sensitive in a braking scenario and therefore tweak the detection system accordingly. A recent development, implemented into this study, are hybrid systems where external lasers and sensors are able to sense when a potential crash is upcoming so that as soon as the brake pedal is touched, the vehicles goes into an emergency braking procedure; however these systems still rely on a human physical response, which is where a mind-reading system could benefit.

V.Relevance for driver monitoring system

Assistance systems that require the driver to (re)act before initiating a safety program currently rely on behavioral markers such as brake pedal deflection and gas pedal release. While this approach ensures that safety measures are not taken against the driver's will, waiting for the driver's response can lead to a slow response in emergency situations. Therefore, in order to obtain a faster confirmation, the studies suggested that it is feasible to detect a driver's intention to brake, which naturally precedes any observable actions.

Many times, it happens that when driver feels very drowsy but he/she tries to keep himself/herself to concentrate on driving which has adverse effects on driving performance. In such situation, we can design an automatic braking system which will check for driver inattention and informs the driver. And when driver doesn't respond in time the automatic brakes will be applied.

Another application can be in case of drunken driving. Drunken driving is the act of operating or driving a motor vehicle while under the influence of alcohol or drugs to the degree that mental and motor skills are impaired. This is a severe issue in case of traffic accident. If a person is taking alcohol and if he is in abnormal condition then the attention level from the EEG signal will get changed than the normal condition. In such situation, the drunken state of driver will be checked just when he is about to start his/her car. And if EEG signals are found to be abnormal, we can design the system such that the engine of the car will not be started. This will reduce the number of accidents due to drunken driving.

The EEG system has to cope with a multitude of artifacts that are stronger than the neural signals. For example, there are mechanical artifacts induced by electrode motion, which can result from unsteady direction of motion of the vehicle (e.g. when entering a sharp curve) or by head and body movements of the driver. Moreover, electrical activity of head muscles, e.g. caused by chewing, raising eyebrows or eye blinking might be more prevalent during real driving. Presently, it is unclear whether;

(a) the signal quality in real-world recordings will be significantly degraded compared to the laboratory setting,

(b) this would also lead to deteriorating detection performance and

(c) in this case, advanced data analysis methods such as independent component analysis artifact reduction may help to overcome such problems.

Another issue regarding EEG technology concerns its practical applicability. Current systems are based on electrode caps that are uncomfortable to wear, unattractive and involve the application of abrasive gel to the skin. Furthermore, a 64-electrode system as used here requires time-consuming preparation. However, significant advances have been made recently, e.g. in the development of dry electrodes. With respect to wearing comfort, new miniature electrodes that can be mounted capless (using only one droplet of gel per electrode) promise to be virtually unnoticeable in practice. Moreover, commercial wireless EEG systems are already available.

VI. PROPOSED SYSTEM

Figure below shows the block diagram for the proposed system.

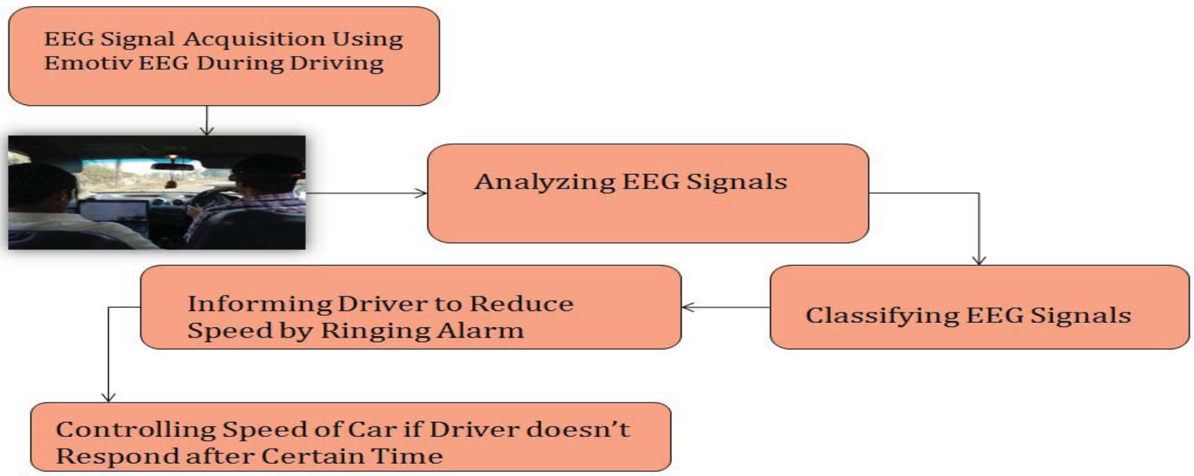

Fig.1 Block Diagram of proposed System

The proposed system tests the driving of participants on Different traffic environment. During the experiment few questions will be asked to the participants, which relate the stress level of a person or they can be asked to remember the situation in which they tend to drive fast. The situation can be like

- getting late for work
- attending best friend marriage and many such situation where they tend to drive faster

In the mean time, EEG signal will be acquired using Emotiv headset and these signals will be acquired on Emotiv Control Panel and EEG Signal can be viewed and recorded on Emotiv Testbench software. These signals will be processed and divided into different band of frequencies as shown in Fig.2. The next part is feature selection. The different frequency band contains different features, out of which the one which contains more information about the state of driver, will be selected and extracted. These signals will be analyzed and driver's mental state will be predicted. If system founds that driver is not mentally stable, it will ring the alarm indicating that driver is not mentally fit for driving.

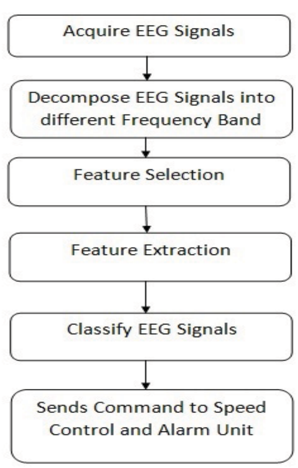

Fig.2 Algorithm for the Proposed System

VII. SCOPE FOR FUTURE WORK

Implementing the EEG based Driver Assistant System in real time is challengeable task because there is significant delay in recording EEG signal and making the system to respond on that. Also designing the system with wireless EEG system would be another issue for development of EEG based Driver Monitoring System. Although there are challenges to deal with but if such system finds application in real world that will definitely reduce number of accidents on road.

VIII. CONCLUSION

Although tremendous work has been done on driver's fatigue detection but those work has been based on image processing or physiological signal such as electromyography (EMG) in which a system continuously monitors the driver's face and evaluates the fatigue level. If we can tap into drivers' brain signals and develop a system which responses on those signals, it will be of great use. To the date, very few research groups are working in this field but surely in the coming time many research scholars will starts doing work in this field.

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