Spectral Characteristics Assessment in Recognition of Drivers' Drowsiness Using Statistical Tests

S. N. Miri Ashtiani, Z. Mardi, and M. Mikaili

***Abstract*—One of the main causes of traffic accidents is drowsiness while driving. Since brain signal (EEG) can report the brain state and its activity momentarily and simultaneously, many researches have been focused on EEG signal for detecting the driver's alertness state. In this study, multichannel EEG signal was recorded from 10 volunteers when each person played a driving game in a virtual environment passing barriers in the game. These subjects should stay awake for at least 20 hours before the test. Process of recording signal for each subject during the driving game lasted about 45 minutes. After the preprocessing and manual labeling of gathered EEG data and extracting spectral features, using paired sample *t*-test we showed which of these frequency characteristics can create a significant difference up to 95% between alertness and drowsiness signals, and in the future studies can be used as indexes for drowsiness in order to increase the drivers' safety.**

I. Introduction

Sleep is an organized behavior for coordination the body rhythm and the daily living which is repeated everyday. Some of its characteristics are relative immobility and notable increase in response threshold to external stimuli comparing to the alertness state. Sleep and rest are some of physiological and basic needs of human being and if they are not met, the human life will be endangered. Although technology has made a lot of changes in our life but the human physiology has not been evolved and still our lives depend on the night sleep and the day work in accordance to the physiological hour or circadian program.

Sleep loss can affect the aspects of human abilities and capabilities [1]. Drowsiness affects on the reaction time (which is one of the vital parameters for a safe driving). Moreover the care, vigilance, awareness level and ability to perform activities requiring concentration and attention (such as driving) also hurt [2].

Reviews show that the number of killed or injured persons in accidents results by drowsiness is approximately 50% of the total number of accidents. In order to promote the road traffic safety, this factor shall be treated as a scientific-executive case and the factors resulting to drowsiness and its signs are identified and consequently the activities are made for preventing accidents and reducing the probable injuries.

A number of methods have been proposed to detect sleepiness condition. In a general analysis, the used methods can be classified into three major categories, including the driver's driving pattern, driver monitoring system based on image processing and the detecting system for drowsy driving using measurement of physiological indicators of driver. The studies made for these classifications are as follows: Ueno, H., Kaneda, M., & Tsukino, M. (1994) developed a system that uses image processing technology and alertness is detected on the basis of the degree to which the driver's eyes are open or closed. In 1998, Boverie, S., Leqellec, J. M., & Hirl, A described a new aproach for driver's drowsiness detection based on analysis of their eyelid movement. Grace, R. introduced a system with an audible tone. The alarm tone triggers are associated with PERCLOS calculated over three minutes [3].

Time series of interhemispheric and intrahemispheric cross spectral densities of full spectrum EEG is another study in 2001 by Aleksandra Vuckovic *et.al* They used three types of artificial neural networks: (1) the linear network; (2) the non-linear ANN; and (3) the Learning Vector Quantization (LVQ) neural network that gave the best results in classification about 94.37% [4].

Chin-Teng Lin *et.al* (2005) proposed a new approach for drowsiness detection based on combination of electroencephalogram (EEG) power spectra estimation, independent component analysis and fuzzy neural network in a dynamic virtual-reality-based driving environment [5].

At the same year, Abdulhamit Subasi used wavelet method and extracting some statistical features from wavelet sub bands. He used artificial neural networks for classification. Total accuracy in this study for alertness, drowsiness and sleep detection by ANN was above 92% [6].

Christos Papadelis *et.al* in 2006 used the Relative Band Ratio (RBR) of the EEG frequency bands, the Shannon Entropy, and the Kullback-Leibler (KL) Entropy were estimated for each one second segment, and statistical tests for drowsiness detection [7]. In 2007 Hisashi Yoshida *et.al* proposed a new method for analyzing brain activity from Electroencephalogram (EEG) based on a concept of instantaneous equivalent bandwidths (IEBWs) to track bandwidths changes of EEG signals. This method used positive time-frequency distributions [8]. Investigation of the relationship between changes in the electroencephalogram (EEG) and slow eye movements (SEMs) in the electro-

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oculogram (EOG) at the wake-sleep transition is another study in 2007, wavelet transform and energy functions were used in this study, and SEMs are detected automatically by a computerized system [9].

Another study in 2007 was focused on total variant of EEG signal with reduced number of channels. For detailed classification of drowsiness, authors used alpha waves [1]. An article published in 2008, Hu Shuyan , Zheng Gangtie tried to predict of drowsiness by employing support vector machines with eyelid related parameters extracted from EOG data. The accuracy of drowsiness detection for very sleepy peoples is quite high [3]. Emmanouil Michail *et.al* (2008) demonstrated that power spectral analysis of driver's heart rate and changes in fractal dimension of EEG signal are associated with driving errors [10]. Another paper in 2008 decomposed EEG signal to sub bands by wavelet transform and then extracted Shannon entropy of each sub bands. Average accuracy of alert and drowsy and sleep classification by usage of ANFIS is above 98% [11].

Another method was dynamic clastering that was introduced in 2008. this method was based on EEG to estimate vigilance states and used temporal series information to supervise EEG data clustering [12]. Muhammed B. Kurt et.al(2009), used wavelet transform for decomposition of EEG signal to its sub bands. For increasing the accuracy of diagnosing the transition from wakefulness to sleep, they applied EEG sub bands and left and right EOG and chin EMG to artificial neural network. Accuracy of classification was above 97% for sleep, alert and drowsy stats [13]. Finally in 2009, Mervyn V.M. Yeo et. al shown that support vector machines are the best classifier for diagnosing wake to sleep transition. Samples of EEG data from both states were used to train the SVM program [14].

In this study, EEG signal has been recorded with a new protocol based on the conditions of driving using a virtual simulation. After data acquisition, with extracting the spectral features from the recorded signals, a statistical analysis was applied for evaluating the fitness of each feature in discriminating between alertness and drowsiness states.

II. MATERIAL AND METHODS

A. Participants

In this experiment, 10 subjects from the students of Master of Science (M.Sc.) of Shahed University (engineering faculty), including 3 females and 7 males participated. The age average of participants was 27.67 years, with average 8 years of driving experience. These subjects should stay awake for about 20 hours before the test and do not consume any drowsiness-causing medications and caffeinated drinks at least 3 days before the experiment. It should be mentioned that all the subjects were selected among committed persons who had accepted and met all the strict instructions. The Epworth Sleepiness Scale (ESS) (John, 1991) [15] was used in order to identify and determine the level of daytime sleepiness of the subjects. Total score in Epworth test is 24 that indicate severe sleepiness. But Epworth scores for selected subjects were in range of normal alertness (below 8) and mild drowsiness (between 8 and 11).

B. Data Acquisition

1) EEG Equipment and Data Collection

The portable EEG equipment used was a 24-channel NCC (Z2N-24W) system, with a sampling frequency of 128Hz. Because of long time recordings, electrode cap with two gels for cleaning the head skin and connecting were used. EEG signal recording was done using standard 10/20 system of electrode placement and we recorded left eye EOG signal simultaneously, for removing eye blink artifacts.

2) Driving Simulation Tasks

Since recording of the data must be done in virtual driving condition and subjects should feel drowsiness, therefore we decided to use a simple driving game with low excitement. This game should be able to show times of passing and crashing to the barriers existed on monitor. This game had been formed as 2D, a straight and monotonous road with the lowest diversity of colors (as shown in the Fig.1). Before starting the game, temporal period for barriers, were entered as an input by operator. These barriers were square shape and appeared on monitor according to Poisson distribution. If the driver could pass the barriers without hitting them, the passing times as PASS were saved in a separate file as the game output. But if there was a crash, this time was also saved as CRASH on that file. By an automatic alarm, the subjects could be aware of driving event and it could make them alert. After the game ended, we could be informed about the crash and pass times for each subject, accessing the above mentioned file.

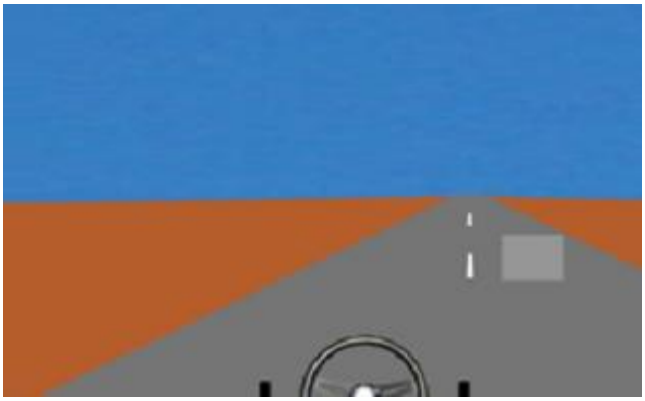

Fig. 1. Simulated driving environment

Data collection was done in a quiet laboratory circumference with normal luminosity. During the EEG data collection we were recording videos of faces and eyes of subjects, by a webcam installed on computer of driving game. For each subject there was 3 to 4 record sessions, and each of them lasted about 45 minutes in average.

Before the test, personal information and all necessary knowledge about recordings were saved for each subject as a

document. And at the end of the record process, the subjects described their conditions during the driving game in virtual environment as much as possible.

C. Data Preparation

1) EEG Filtering and Artifacts Rejection

For data preparation, a band pass filter with a frequency range of 0.5 to 30Hz and a Notch filter at the 50Hz power supply component were used. The band pass filter was a Chebyshev type 1 and order 2. Then EEG signals were divided into 2-second segments (256 samples) without overlapping. The movement artifacts were also removed visually.

2) Data Manual Labeling

Video recording were simultaneous with data recording and driving game; so we used pass and crash times of driving game for manual labeling of EEG datasets. Fig.2 shows the labeling procedure.

Therefore at first, using the game's output file, The occurred CRASH or PASS times were marked in each 2s epochs. For example, If crash was happened at the end of epoch, we considered this and previous epoch as drowsiness. But subsequent epoch was labeled as alertness, because of alarm.

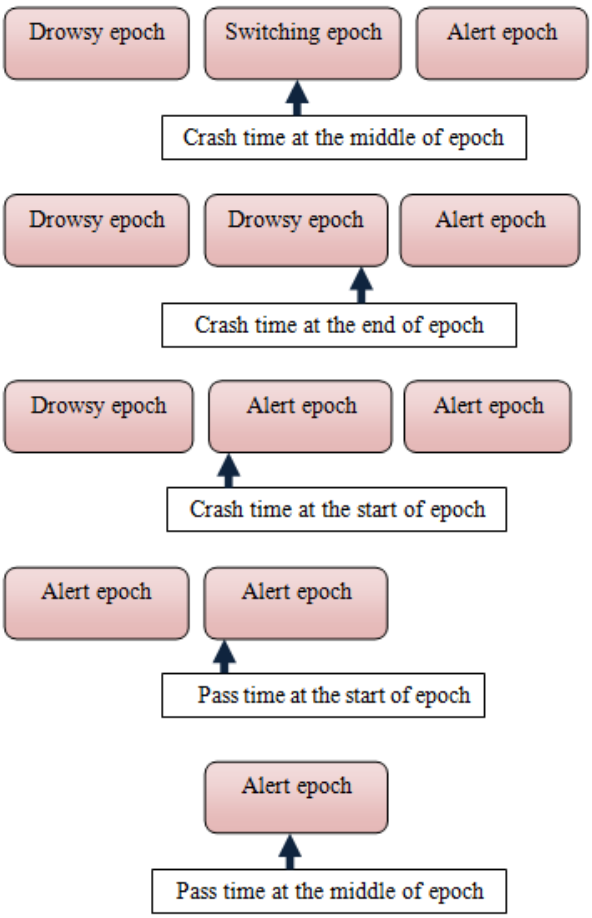

Fig. 2. Labeling steps of 2second epochs of recorded EEG by using driving game's output.

Finally in order to make sure about the accuracy of mentioned labeling, we used video recordings and subjects' descriptions about their conditions during the virtual driving. For example if a subject passed a barrier, but according to the video recording he or she was drowsy during the passing, we discarded corresponding EEG, and if a subject crashed to a barrier but he or she said that this event was happened in vigilance, corresponding EEG was discarded, with due attention to recorded video.

D. Data Analysis

After labeling process, it is time to extract measurable characteristics from EEG signal, particularly signal frequency parameters in order to analyze datasets.

To achieve this, a fast Fourier transform (FFT) [16] with a rectangular window using 256 data points without overlapping was performed on each channel of a 2-s EEG data epoch. The resulting power spectrum density function was divided into 4 segments according to the 4 major EEG frequency bands: delta, theta, alpha and beta waves [17]. After signal power spectrum estimation, the following features were extracted from each channel for each frequency band.

1) Relative Power of Frequency Bands

If we consider the recorded EEG signal as x, the power spectrum density of x can be obtained after the FFT.

The sampling frequency (f_s) of the used instrument in this study was 128 Hz and we used a 256-point FFT, therefore the frequency resolution will be 0.5 Hz.

After FFT, we got $X(k)$ (k=1, 2, 3... 255), and the power spectrum density was defined by (1):

$$P(k) = \frac{X(k).\overline{X}(k)}{N} \tag{1}$$

Where N=256 (the number of sampling points in the FFT).

According to the frequency range of 4 standard EEG frequency bands, the relative power can be set by (2):

$$\begin{aligned} P_\delta &= \frac{\sum P(i)}{P(k)}, 0.5 \le f(i) \le 3.5 \\ P_\theta &= \frac{\sum P(i)}{P(k)}, 4 \le f(i) \le 8 \\ P_\alpha &= \frac{\sum P(i)}{P(k)}, 8.5 \le f(i) \le 13 \\ P_\beta &= \frac{\sum P(i)}{P(k)}, 13.5 \le f(i) \le 30 \end{aligned} \tag{2}$$

Where i=1, 2, 3 …, $\frac{N}{2}$, $f(i)$ can be calculated by (3):

$$f(i) = \frac{f_s \times i}{N} \tag{3}$$

2) Drowsiness Index

Considering that the transition from vigilance to sleep is appeared as a change in brain rhythm from beta (vigilance) to theta (sleep stages) [1], [14] therefore, the drowsiness index gotten by (4) can be considered as a characteristic for evaluating the state of driver's drowsiness:

$$Drowsiness\ Index = \frac{P_\theta}{P_\beta} \tag{4}$$

Where P_θ and P_β are the relative power of theta and beta bands respectively.

3) Dual Compositions of Frequency Bands

The dual compositions of the four discussed frequency bands (delta, theta, alpha and beta waves) are as follows:

$$\begin{aligned}
&1.(P_\alpha - P_\beta)/(P_\alpha + P_\beta)\\
&2.(P_\alpha - P_\delta)/(P_\alpha + P_\delta)\\
&3.(P_\alpha - P_\theta)/(P_\alpha + P_\theta)\\
&4.(P_\beta - P_\delta)/(P_\beta + P_\delta)\\
&5.(P_\beta - P_\theta)/(P_\beta + P_\theta)\\
&6.(P_\delta - P_\theta)/(P_\delta + P_\theta)
\end{aligned} \tag{5}$$

III. Results

As mentioned in the previous section, for data analysis, the proposed features were extracted. In this step, there were 840 observations for each class of alertness and drowsiness in 19 channels. Each observation was 2 seconds (256 samples).

Ability of extracted features in alertness and drowsiness detection can be evaluated with statistical tests. Therefore, we have used paired sample *t*-test for each feature in all recorded channels (19 channels). *T*-test can determine the significance level of difference of each feature's average in the two alertness and drowsiness groups.

According to the results of the test, the relative power of beta band shows significant difference with the $p < 0.05$ between the 2 groups for each recorded channel. Also the relative power of theta band shows the same result in most of the channels (except FP1 and FP2).

P-values of *t*-test demonstrate that difference between drowsiness index in alertness and drowsiness is significant in all channels.

This test shows that compositions Nos. 4 & 5 in dual compositions of frequency bands can be statistically distinguished features in our dataset between two alertness and drowsiness classes.

Since alert EEG has been marked with beta activity [14] and drowsy EEG has been marked with theta activity and in deeper stages has been marked with delta activity [1], the obtained results in this study are also confirming this matter.

For visual evaluation of ability of selected features in distinguishing drowsy and alert classes, we computed mean of beta and theta relative powers and drowsiness index over trials for each channel. Then we have plotted them according to channels in Figs. 3, 4 and 5.

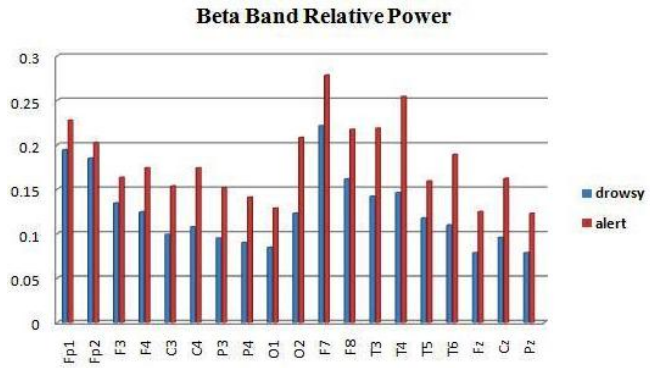

Fig. 3. The mean values of beta band relative power over trials in recorded channels.

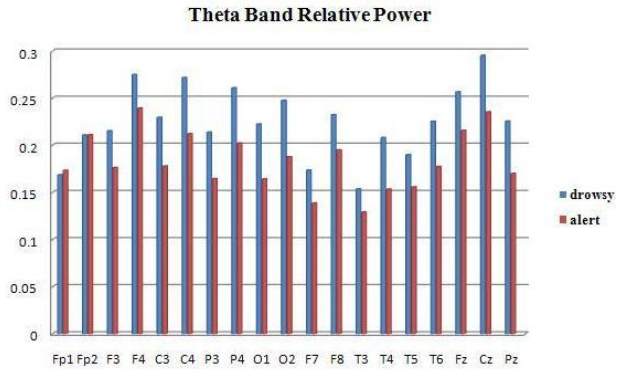

Fig. 4. The mean values of theta band relative power over trials in recorded channels.

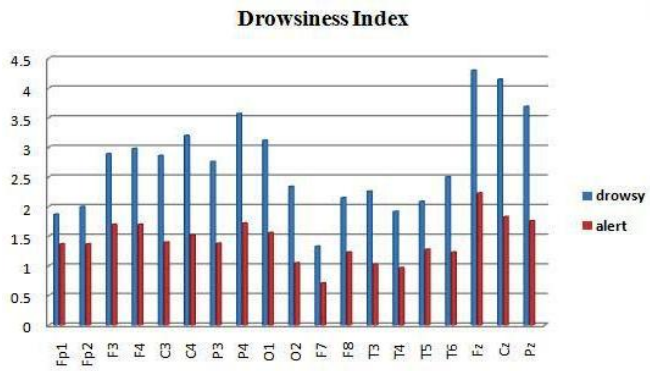

Fig. 5. The mean values of drowsiness index feature over trials in recorded channels.

It is considerable that mean of relative power of beta band over trials, in alert subjects is higher than drowsiness. So it can confirm that beta wave activates in waking condition. Theta and delta waves also are generally correlated with sleep condition. As is shown in Fig. 4, the mean of relative power of theta band over trials, in alert subjects is lower than drowsiness and in the Fig. 5; the drowsiness index values in

sleepiness state are significantly higher than normal driving situation. Therefore, we can conclude that in sleep onset, the brain works with low activity and low energy, so it can be a main reason for car accidents that occur because of drowsiness.

IV. Conclusion

In this study, we have tried to introduce a new protocol for recording brain signal from drowsiness drivers. We have recorded EEG data in a virtual driving environment and tried to create driving conditions based on reality. After recording the EEG and EOG signals and also video recording synchronously, we did some preprocessing on dataset and manual labeling of them.

In this research, the EEG data were analyzed by using the major EEG frequency bands and furthermore by using degree of drowsiness. Each of these features were analyzed separately and by applying paired sample *t*-test we achieved which of these characteristics shows a significant difference with *p*-values below 0.05 between two alertness and drowsiness groups.

Among the proposed features, drowsiness index, relative power of theta and beta and combination of power in the theta and delta waves with beta in dual compositions of frequency bands were more differential in the discrimination of alertness and drowsiness signals. Therefore this category of characteristics has been seemed suitable candidate for detecting of drowsiness.

According to Figs. 3, 4 and 5, by comparing the mean of beta and theta relative powers and drowsiness index over trials, we can find that decreased beta relative power can be observed obviously in the drowsy subjects, while theta relative power of drowsy subjects was significantly increased. As we know, the beta rhythm is fast rhythm and the theta rhythm is slow rhythm in brain waves. As a conclusion, the power of drowsy subjects in slow rhythm was higher than the alert subjects. This demonstrates that under the influences of drowsiness, the brain works with low activity and low energy. So driving in this situation may lead to higher risk of accidents.

The drowsiness index value of drowsy driving calculated by (4) was significantly greater than normal driving, so it can be introduced to evaluate the degree of sleepiness.

Our findings agree with previous researches that EEG signal frequency bands (particularly beta and theta) are very useful in drowsiness analysis and can be used as indexes in order to development of a drowsiness countermeasure system.

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