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A new approach for somnolence detection & analysis based on LabVIEW

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Abstract: Drowsiness is the state where a person is almost asleep or very lightly asleep. It refers to an inability to keep awake. In this thesis drowsiness and sleepiness are considered synonymous, but the term drowsiness will be used. Another concept commonly used is fatigue, which is an extreme tiredness that comes from physical or mental activity. Drowsiness can also be described by the grade of wakefulness or vigilance. Wakefulness is the same as alertness or a state of sleep inability, whereas vigilance can be defined as watchfulness or a state where one is prepared for something to happen. There are several factors which affect the grade of wakefulness. The time spent to carry out a task (time on task) and the amount of sleep during night are the most important factors. Other factors which are responsible are the amount of light, sound, temperature and oxygen content. Motivation and monotony of the task will also have an effect on the grade of wakefulness. Drowsiness can be measured by using physiological measures, performance measures, self-report or expert ratings. In the present trend suggests driving and navigation support systems are getting importance because it is crucial in supporting drivers in several conditions in automobile industry. It is important for driving support systems to detect the status/activity of driver’s consciousness. Detecting onset of driver fatigue could prevent the accidents caused by drowsy driving. It is proposed to detect / analyse the driver fatigue by the application of dedicated physiological indicators such as electroencephalography and also facial features such as eyelid movements based on template matching using neural network technique for closed eyes versus opened eyes. EEG signal is one of the most predictive and reliable measurements by the analysis of alpha, beta and theta band power etc., which are considered as direct factors associated with human drowsiness. The parameters such as blink duration and opening time changes reliably with increasing drowsiness.in this system LabView is used for analysing the data for this application.

Keywords: Drowsiness,EEG, LabView

INTRODUCTION

The ability of a person to remain alert and make decisions quickly decreases considerably during the drowsiness stage. This situation presents a potentially problem in drivers. It is important to characterize the drowsiness and to develop automatic detectors of this stage, in order to avoid and reduce the drastic number of crashes and traffic accidents caused for this reason. Reliable detection of drowsiness is one of the leading objectives in the development of new Advanced Driver Assistance systems. Some of the automatic detection methods are based on studying the driver behavior and the driving performance [3,4]. However, their parameters easily vary according to different vehicle types and driving conditions. Other research groups have proposed techniques based on head and eye movement [5,6], using a camera to acquire the images. Monitoring is good but difficult to commercially promote since nearly all drivers dislike being monitored with a camera directly focusing on their bodies all the time [3]. There are also methods that employ biomedical signal processing to detect drowsiness [7–13] found in related literature. Biomedical signals are especially useful to collect information from the body’s response during the drowsiness cycle. Some authors use the electrocardiographic [11] or electro-oculographic signals [12]. Electroencephalography (EEG) is the most-widely used technique to measure the electrical activity of the brain [14], and is the standard technique in sleep studies. Several authors have proposed the analysis of EEG

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to identify the Drowsiness Stage (DS) [7–10]. The disadvantage of techniques based on biomedical signals is that they require sensors and cables on the body, but it could be easily solved by placing new wireless sensors in a non-intrusive system [13]. Brain electric activity shows characteristic wave patterns in some states, and their differences between being awake and asleep have been studied intensively [15,16]. Different EEG signal processing techniques have been used to identify DS. In Papadelis et al. [9], the relative bands ratio (RBR) of EEG and different types of entropies were using 8 EEG and several EOG, EMG and ECG channels.

Nikhil and co-workers [17] found that the power spectrum of Alpha band in the EEG is correlated with the lost of alertness in drivers. In the experiment they used 34 EEG/EOG/ECG electrodes. Researchers like Makeig et al. [18] and Jung et al. [19] have also implemented the spectral analysis of EEG records using 33 and 2 channels of EOG, respectively. Most of the aforementioned techniques involve complex mathematical processes, or require a large number of syatems

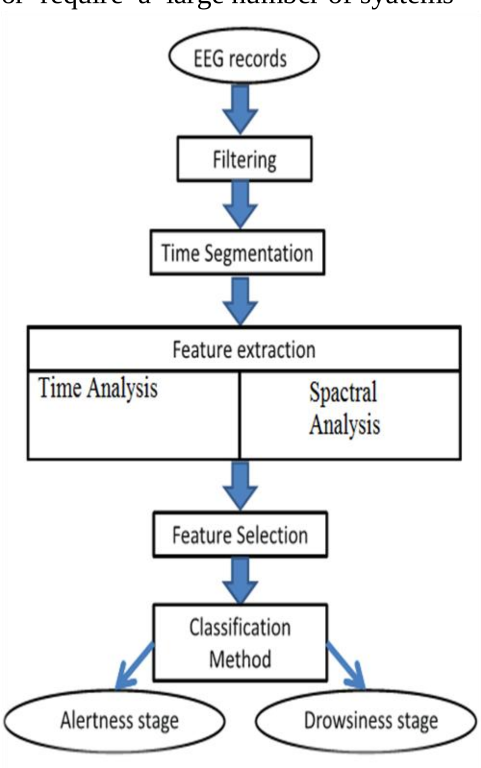

Fig 1: Block diagram of the algorithm

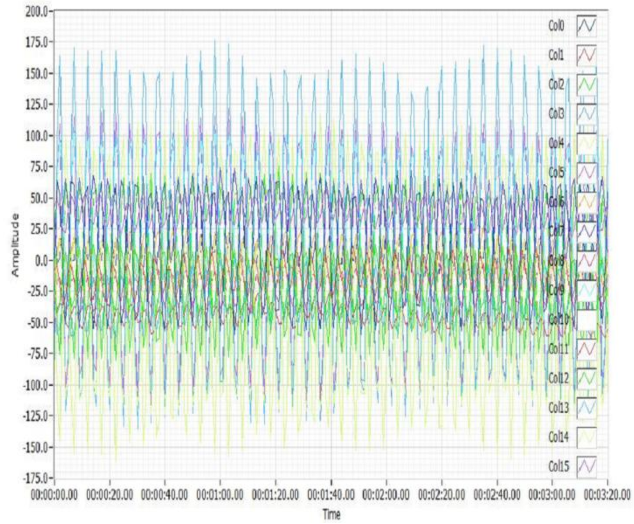

Fig 2: Raw Signal Received From The EEG Machine

MATERIALS

The EEG records of on different subjects were taken. The channels used in the database are O1-T5 and CZ-C3 C3-O1, C4-A1 and O2-A1 on the 10–20 montage system. The sampling frequency is 250 Hz. The sleep stages are scored by experts. The epochs labelled as “Awake stage” and “Stage I” (S1) have been used in this work.

Methods

Fig. 1 shows the block diagram of the proposed algorithm. The process begins with the filtering of the brain rhythm followed by the time segmentation stage. Next the feature extraction and the spectral analysis.Fig 1 shows the signal acquired from 16 channel EEG machine complete signal is of 45 minutes converted in to excel form then from this signal only three electrodes are picked as alpha signal is correlated to the drowsiness.

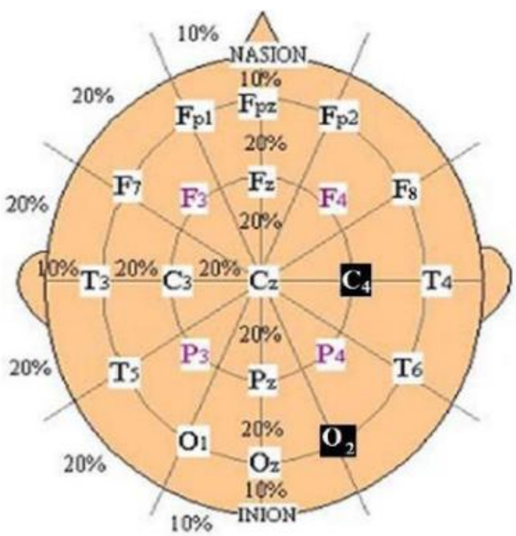

Fig:3 10-20 Electrode system for the EEG Signal Acquire

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3.1. Filtering

The signals were filtered with a 2nd order, bidirectional, Butterworth, band-pass filter with cut-off frequencies of 0.5–60 Hz. Then the biological noise and line interferences were removed from the records.These filters could be implemented in a real car driving situation and the different stages of the cascade would be feed on line with the actual artifacts present in a car, like biological signal of the driver or electrical interferences of the vehicle.

3.2. Time segmentation

The 100 s segmentation of the EEG was done for the further analysis, according to the results of a previous work. This process assures statistical stationary needed for the estimation of the Power Spectral Density (PSD).

3.3. Feature extraction

The activity of the brain is divided into frequency bands, named: Delta (0.5–4 Hz), Theta (4–8 Hz), Alpha (8–12 Hz), Beta (12–30 Hz) and Gamma (over 30 Hz), [28]. In this paper, there have been obtain 19 features from time and spectral analysis.

3.4. Decomposition

The basic features of the signal are extracted using LabVIEW biomedical workbench and bio signal viewer. Further statistical parameters are concluded like minimum value maximum value, standard deviation, variance, and mean value of both of the signals filtered and non-filtered signal.Itegrated EEG (IEEG) as features of each segment were extracted. They are defined as follows:

$$\text{IEEG} = \sum_{K-1}^{N} |d_{i[k]}|$$

$$\text{ZC} = \sum_{k-1}^{N-1} [sgn(-d_i[k+1]d_i[k])]$$

where

$$sgn = \begin{cases} 0, & \text{if } d_i < 0 \\ 1, & \text{if } d_i \geq 0 \end{cases}$$

where di[k] are the samples of each decomposition EEG segments and N is the total number of samples in each epoch.

Discussion

This work, presented an analysis of time, spectral and wavelet features of brain rhythms, to identify difference between awake and drowsy state in EEG signals. Then, it was proposed an automatic method to distinguish Awake State from Drowsy State using EEG features. The advantage of using only one EEG channel is that the driver would use only one pair electrodes in the head instead of using an uncomfortable cap with numerous electrodes. The EEG signal reflects the loss of alertness. well, so it is appropriate to detect drowsiness and prevent accident.

The following table shows the raw EEG signal.
The table shows input signal to obtained from the EEG Machine as alpha wave is the most important factor in the drowsiness detection which can be obtained from the O1-T5 and T4-C4 signals.

Table 1: Signal from various electrode pairs

F8 - F4	F4 - FZ	FZ - F3	F3 - F7	T4 - C4	C4 - CZ	CZ - C3	C3 - T3	T6 - P4	P4 - PZ	PZ - P3	P3 - T5	T6 - O2	O2 - PZ	PZ - O1	O1 - T5
-4	-3	-7	4	4	-4	2	-2	0	-1	7	-3	5	-7	3	1
-4	-2	-9	4	3	-3	2	-2	0	-2	8	-4	6	-8	3	1
-2	-2	-11	5	2	-3	2	-1	-1	-2	9	-4	7	-9	4	1
1	0	-14	5	2	-3	2	-1	-1	-2	10	-4	8	-10	3	3
1	0	-15	7	2	-2	2	-1	-1	-2	11	-3	10	-12	3	6
0	-1	-15	10	2	-2	1	-1	-1	-2	14	-2	14	-16	2	10
1	-3	-14	13	2	-2	1	0	-1	-1	16	-1	17	-19	2	12

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3	-4	-14	14	2	-2	0	0	-1	-1	17	-1	17	-20	2	13
4	-4	-13	13	1	-1	0	1	-1	-1	16	-2	16	-18	2	12
2	-3	-13	11	1	-1	0	2	0	-1	14	0	16	-17	1	12
-3	-2	-12	12	1	0	0	4	0	-1	13	2	17	-18	0	14
-10	-2	-12	14	2	0	1	6	0	-1	13	3	19	-19	0	17
-14	-2	-11	17	2	0	0	7	0	-1	14	4	20	-21	-1	18
-13	-3	-10	17	2	0	-1	7	1	-1	14	3	21	-21	-1	18
-9	-4	-11	16	1	0	-2	6	1	-1	16	2	20	-20	0	17
-7	-5	-11	14	1	0	-2	5	1	-1	19	0	22	-22	2	16
-8	-5	-11	13	1	0	-2	4	1	-1	22	-2	24	-24	3	17
-11	-4	-9	13	0	0	-3	3	2	-1	24	-3	26	-25	3	18

RESULTS

EEG Sample numbers are noted down in the excel file for drowsy state using "Take Samples" utility 87 Samples with both Awake and Drowsy state are used to train Neural Network for Pattern recognition. Below is the signal awake state:

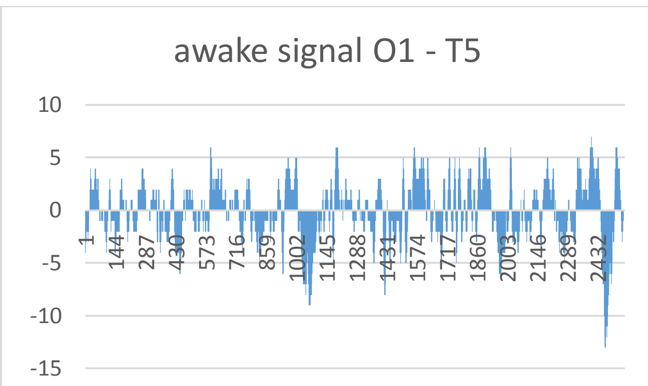

Fig: 4 Showing the input signal for electrode O1-T5 Alpha signal

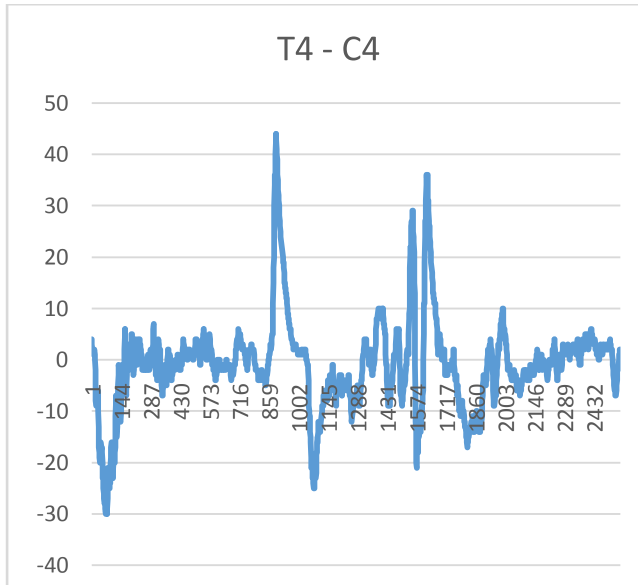

Fig 6:Raw signal for T4-C4 pair of electrodes

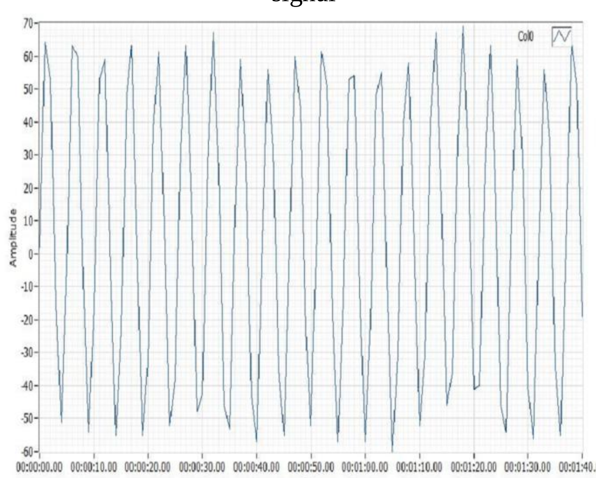

Fig 5: Showing the signal recording for O1-T5 pair of electrodes

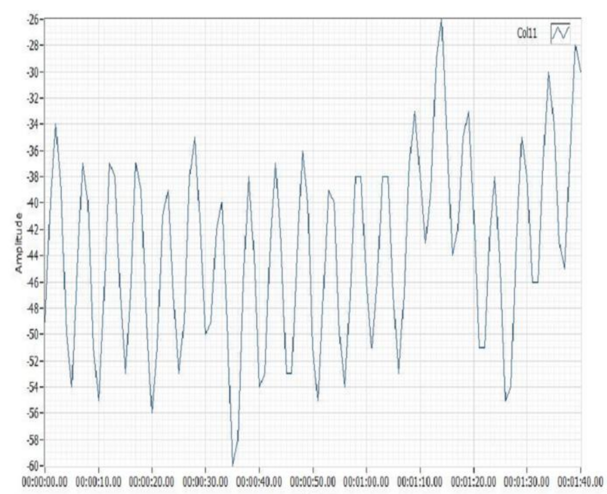

Fig 7: Output of the T4-C4 pair of electrodes

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CONCLUSIONS

Techniques used in feature extraction and classification of EEG waveform in time and frequency domain have been briefly reviewed in this paper. Result shows clear differentiation of the frequency distribution of the EEG waveform.

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