Available Online at www.ijcsmc.com

International Journal of Computer Science and Mobile Computing

A Monthly Journal of Computer Science and Information Technology

ISSN 2320–088X

IJCSMC, Vol. 2, Issue. 12, December 2013, pg.448 – 455

RESEARCH ARTICLE

Monitoring Driver Alertness and Avoiding Traffic Collision Using WSN

B.Arunkumar[1], N.Deepak[2], Dr.T.V.P.Sundararajan[3]

[1]P.G Scholar, Electronics and communication Engineering & Anna University, India
[2]P.G Scholar, Electronics and communication Engineering & Anna University, India
[3]Professor, Electronics and communication Engineering & Anna University, India
[1] arunkumarb.ae12@bitsathy.ac.in; [2] deepakn.ae12@bitsathy.ac.in; [3] suntvp@bitsathy.ac.in

Abstract- Driver drowsiness is among the leading causal factors in traffic accidents occurring worldwide. This paper delineates a method to monitor driver safety by analyzing information related to fatigue using EEG signals. Drowsiness is a state of near-sleep, a strong desire for sleep, or sleeping for unusually long periods. It is also the transition state between awakening and sleep during which a decrease in vigilance is generally observed. Both behavioral and physiological modifications occur during drowsiness. Reaction time is slower, vigilance is reduced and information processing is less efficient, which can generate abnormal driving; it induces an increase of the number and the duration of blinks and yawns. Changes in cerebral activity also happen. Therefore, a drowsy detector system is developed which detects drowsiness using EEG signals. The EEG signals from different persons are analyzed and the feature extraction is carried out through the method Fast Fourier Transform (FFT).The EEG signals are classified as delta, theta, alpha and beta depends on these frequency values to detect driver fatigue and to alert the person.

Keywords – Electroencephalogram (EEG) signals; Independent component analysis (ICA); Fast Fourier Transform (FFT).

I INTRODUCTION

The development of a human drowsy state monitoring system for drivers has become a major focus in the field of safety driving and accident prevention because drivers fatigue has been implicated as a causal factor in many car accidents.

Many studies related to drowsy state monitoring and detection technologies have been developed during the last decade. Kozak et al. [1] and Rimini-Doering et al. [2] proposed a similar lane-departure warning system via tracking lane marks by camera systems for the assisted drivers. A different approach is to monitor the activities of the drivers themselves such as yawning, head positions, or eye blink duration by using optical sensors or video cameras [3], [4]. However, image or video-based techniques are sensitive to external weather conditions, e.g., rain or snow, and are easily influenced by the driver's posture inside the car. McGregor et al. [5] introduced a technique to monitor the driver's physiological states by directly acquiring and analyzing subject's heart-rate variability (HRV) and electrooculography (EOG) [6] signal, which can overcome the system disadvantages mentioned above. Nevertheless, the minute-length scale of HRV and EOG analyses limit the monitoring system to a low-temporal-resolution output. Huang et al. [7] demonstrated tonic EEG power increase in low-frequency bands in the occipital cortex during high-error periods in a continuous visual tracking task, and they also showed similar tonic EEG power increase in low-frequency bands in the occipital cortex in simulate driving experiments .

Khushaba et al. maximized the drowsiness-related information extracted from electrooculogram (EOG), EEG and ECG signals to classify driver attentiveness. Lin et al. [8] proposed a brain-computer interface (BCI) system that can analyze EEG signals in real time to monitor a driver's physiological and cognitive states. Yang et al. [9] used a first-order HMM to compute the dynamics of BN for compiling information about multiple physiological characteristics such as ECG and EEG to infer the level of driver fatigue. Giusti et al. [10] designed an intelligent system that compiled physiological data acquired from a sensor on the steering wheel, as well as mechanical data from a simulation platform to evaluate a driver's level of attentiveness.

1. Drowsiness

Drowsiness is the transition state between awakening and sleep during which a decrease of vigilance is generally observed. This can be a serious problem for tasks that need a sustained attention, such as driving. According to a report of the American National Highway Safety Traffic Administration (Royal, 2002) driver drowsiness is annually responsible for about 56,000 crashes, which is the reason why more and more researches have been developed to build automatic detectors of this dangerous state. Both behavioral and physiological modifications occur during drowsiness. Reaction time is slower, vigilance is reduced and information processing is less efficient, which can generate abnormal driving; it induces an increase of the number and the duration of blinks and yawns. Changes in cerebral activity also happen.

The remainder of this paper is organized as follows. Section II explains the existed system of this paper. Section III discusses the results of proposed system in MATLAB. Section IV explained about simulation results. Section V draws some conclusion. Finally, Section VI discusses the future work.

II EXISTED SYSTEM

2. Drowsiness Detection Systems

2.1 Systems Focusing On Vehicle Behavior

The purpose of this system is to detect abnormal behavior of the car due to the driver's drowsiness. These systems use sensors for monitoring certain features of the vehicle's behavior. One of the features is steering wheel grip sensor.

In Fig 2.1, the sensors are placed in the steering wheel. The output of the sensor is given to the ADC0808.The ADC output is given to the microcontroller; here we are going to check the grip values. If the pressure of the driver is reduced in the steering than the normal value for a while microcontroller gives the indication by means of alarm and stop the vehicle after quite bit time. The block diagram for physical behavior system is given below,

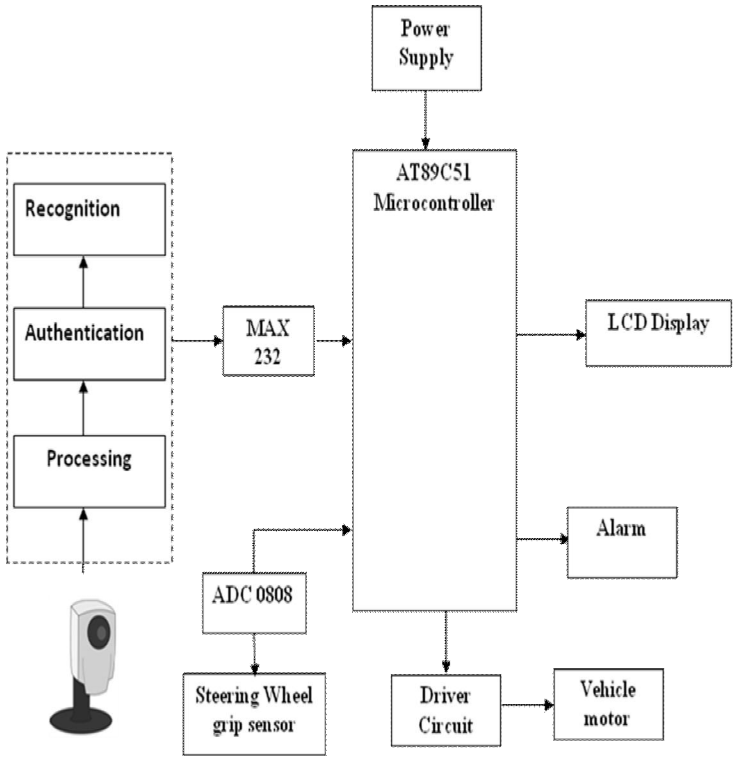


Fig 2.1 Block Diagram

III PROPOSED SYSTEM

3. System structure

The flowchart data processing procedure was illustrated in Fig 3.1 that consists of Independent Component Analysis (ICA), power spectra analysis, and feature extraction.

3.1 Independent Component Analysis

The blind source separation (BSS) problem deserves to be solved in the EEG signal which is usually contaminated by various artifacts including eye movement and indoor power-line noise. One of the popular methods was applied ICA to find the linear projections that maximizes the mutual independences of estimated components. The general representation of ICA model can be simply denoted as $S=W^{-1}\times X$, where $S= [S_1,S_2,\ldots S_N]^T$ presents the n is independent sources, w^{-1} is the back-projection weighting matrix $x=[x_1,x_2,\ldots x_3]^T$ and is the observed signals. The purpose of ICA algorithm is to find out the back-projection weighting matrix, w^{-1},to have a maximum statistically independency of the separated components, . Then, the occipital component was selected by the weighting distribution of the scalp topography, which is rendered by, as the region of interest for power spectra analysis and feature extraction.

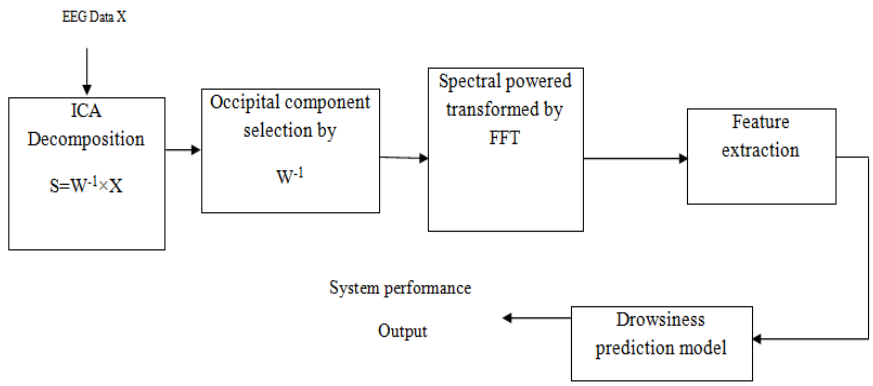


Fig 3.1 Block Diagram

3.2 Power Spectra Analysis

The occipital components were taken for power spectra analysis. In the first step of the spectral transformation, each 1-s length epoch (250 data points) was divided into several 128-point sub epochs by Hanning windows. Then, we perform 256-point FFT with zero-padding for each sub epoch to obtain the power spectral density. Finally, the average of spectral powers of sub epochs was used for the spectral representation of this 1-s length occipital activation. Here, only the spectral powers of the -band (4–7 Hz) and -band (8–12 Hz), which is reported as the significant index for the driving error , with the corresponding RT were used as the dataset pair to establish the prediction model.

3.3 Feature Extraction

This is possibly the most critical step in the signal processing. The goal of this step is to create a manageable and meaningful representation of the original EEG signal (although clean), in order to maximize the potential success of qualifiers and in turn the overall system performance. A second objective of the feature extraction phase is to compress data without loss of relevant information in order to reduce the number of input variables in qualifiers (in order to operate in real time). There are several approaches that may be adopted in the feature extraction phase and actually find just the right to do so is an active target of this thesis.

A simple method of feature extraction is what is called the method "band spectral power" which each channel is applied to a bank of four digital band pass filters. These filters have pass bands centered on four frequency bands in conventional EEG signal analysis: delta waves (0-4 Hz), theta (4-8 Hz), alpha (8-13 Hz) and beta (> 13 Hz). These frequency bands have been studied for decades and are known to represent interesting forms of brain activity. For example, a strong alpha component means that the subject is very relaxed. At the output of this band pass filters the instantaneous power is measured using a moving average filter sliding window. On this way each channel EEG raw signal is transformed into a set of four power measurements that are updated regularly.

This project focuses on getting the four classical frequency bands in EEG signal analysis: delta waves, theta, alpha and beta, but in this case it focuses especially on the alpha, beta and theta waves because what really it is wanted to analyze are micro-sleeps and how they affect in the drivers, therefore, sleep stages to be discussed in this thesis are S0, S1 and S2, which have been explained above. Delta waves have been discarded because they are part of phases of deep sleep which are not part of the analysis. To do this, there are some techniques such as Fast Fourier Transform that are explained below.

3.4 Fast Fourier Transform

Discrete Fourier Transform transforms a mathematical function into another, obtaining a representation in the frequency domain, where the original function is in the time domain. But the DFT requires an input function with a discrete sequence and finite duration. This transformation only evaluates enough frequency components to reconstruct the finite segment which is being analyzed. Using DFT implies that the segment which is being analyzed is a single period of a periodic signal that extends to infinity; if this is not true, it should be used a window to reduce spurious spectrum. For these reasons, it is said that DFT is a Fourier Transform for analysis of discrete time signals and finite domain. Sinusoidal basis functions that arise from decomposition have same properties. The DFT input is a finite sequence of real or complex numbers, so that is ideal for digital signal processing.

3.5 EEG Waveform Representation

Table 3.1 EEG Waveform Representations

SIGNAL	FREQUENCY	ACTIVITY
BETA	Above 13	Power varies according to task difficulty
ALPHA	7-13	Power increases during the sleepiness
THETA	4-7	Power suppresses during the sleepiness
DELTA	1-4	Power increases during deep sleep stage

IV SIMULATION RESULTS

The EEG data analysis and signal processing were implemented by scripts running in MATLAB (R2013a) and the EEGLAB Toolbox developed by the Swartz Center for Computational Neuroscience, the University of California SanDiego (UCSD). Raw data have artifacts and noises because are very sensitive to external factors that are independent of the brain, like for example blinking and movement of eyes, excessive electrodes gel, dried electrodes, broken EEG electrodes, stretching of muscles, etc. These artifacts and noises have been removed applying the appropriate signal preprocessing; in this case, a independent component analysis has been used to make such signal preprocessing.

Independent component analysis (ICA) is a relatively recent method for blind source separation (BSS), which has shown to outperform the classical principal component analysis (PCA) in many applications. Fig 3.1 represented a input signal extracted from predefined data and it is analysis from Independent component analysis. The input signal and ICA analysis of pre processing signals Fig 3.2 are given below,

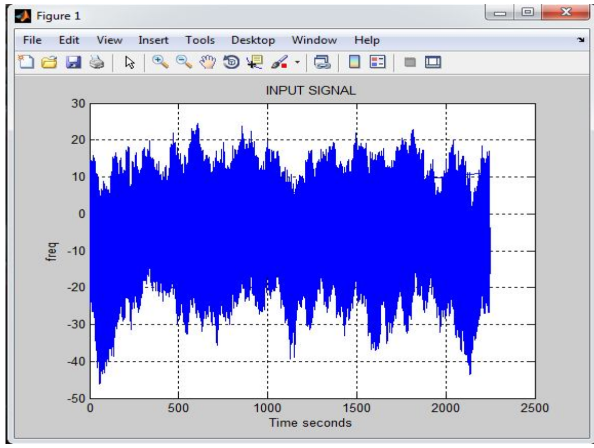


Fig 3.1 Input Signals

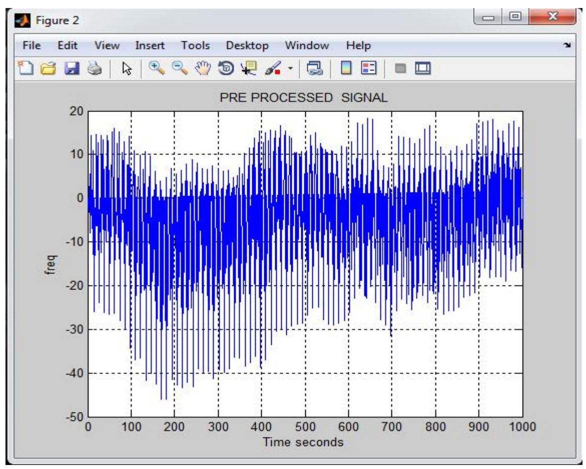
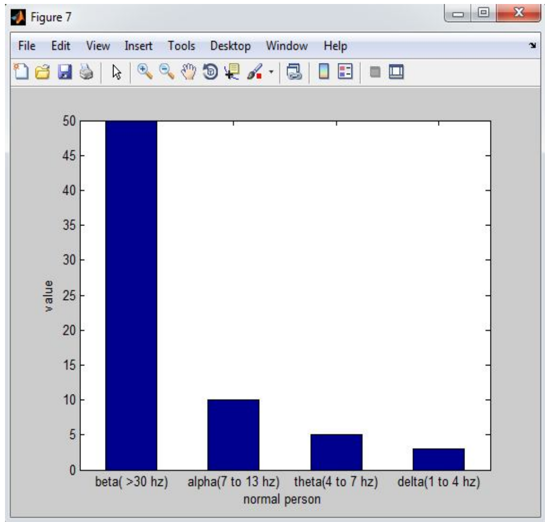


Fig 3.2 Preprocessing Signals

After independent component analysis section the preprocessing signals are applied to the power spectral analysis and feature extraction. A simple method of feature extraction is what is called the method "band spectral power" which each channel is applied to a bank of four digital band pass filters. These filters have pass bands centered on four frequency bands in conventional EEG signal analysis: delta waves (0-4 Hz), theta (4-8 Hz), alpha (8-13 Hz) and beta (> 13 Hz). These frequency bands have been studied for decades and are known to represent interesting forms of brain activity. The main goal of this step consists in divide the signal in different frequency ranges (alpha, beta, theta, delta…).

The Fig 3.3 represented a normal frequency values it's extracted from MATLAB. The values are mentioned in previous EEG signal analysis. The person with drowsiness signals are simulated by using predefined drowsiness data it's also extracted from MATLAB software. The comparison results of normal and drowsiness person is given below,



Normal person

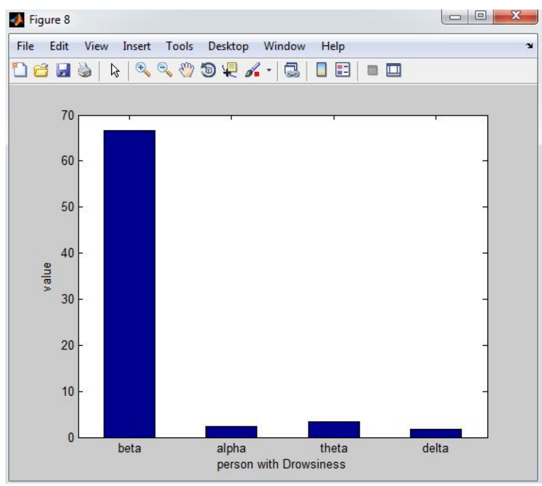


Fig 3.3 Comparisons result of normal and Drowsiness

V CONCLUSION

Driver drowsiness is a major, though elusive, cause of traffic crashes. In this project to monitor driver safety by analyzing information related to fatigue using EEG signals and to avoid the accidents. The EEG signals are decomposed into time–frequency representations using wavelet transform and statistical features are calculated to depict their distribution. A power spectra-based system has been implemented for the classification of EEG signals using the statistical features extracted from wavelet coefficients as inputs. The extracted EEG signals are delta, theta, alpha and beta depends on these frequency values measure the driver fatigue. A warning alarm is applied if driver fatigue is believed to reach a defined threshold.

VI FUTURE WORK

In future work the VANET system is used to avoid pileup problem among the vehicles. The VANET is used here to signal about the accident to the other vehicles, which are all coming in particular surrounding.

REFERENCES

1. K. Kozak, J. Pohl, W. Birk, J. Greenberg, B. Artz, M. Blommer, L. Cathey, and R. Curry, “Evaluation of lane departure warnings for drowsy drivers,” in Proc. Human Factors and Ergonomics Society 50th Annual Meeting, Oct. 16–20, 2006.

2. M. Rimini-Doering, T. Altmueller, and U. Ladstaetter, “Effects of lane Departure warning on drowsy drivers’ performance and state in a simulator,” in Proc. 3rd Int. Driving Symp. Human Factors in Driver Assessment, Training Veh. Design, Rockport, ME, Jun. 27–30, 2005.

3. J. C. Popieul, P. Simon, and P. Loslever, “Using driver’s head movement’s evolution as a drowsiness indicator,” in Proc IEEE Intell. Veh. Symp, 2003.

4. Q. Ji, Z. Zhu, and P. Lan, “Real-time nonintrusive monitoring and prediction of driver fatigue,” IEEE Trans. Veh. Techno, Jul. 2004.

5. D. K. McGregor and J. A. Stern, “Time on task and blink effects on Saccade duration,” Ergonomics, Mar. 1996.

6. F. Zhang, A. Mishra, A. G. Richardson, and B. Otis, “A low power ECoG/EEG processing IC with integrated multiband energy extractor,” IEEE Trans. Circuits Syst. I, Reg. Papers, 2011.

7. R. S. Huang, T. P. Jung, A. Delorme, and S. Makeig, “Tonic and phasic electroencephalographic dynamics during continuous compensatory tracking,” Neuro Image, Feb. 2008.

8. T. Kasukabe, M. Hiraoka, O. Yamamoto, M. Yamada, and T. Nakano, “Development of system for comprehensively measuring driving ability for elderly safe driving,” in Proc. Conf. Mach. Vis. Appl., Yokohama, Japan, May 2009.

9. Yang, B.; Huang, Y.-Z. A study on drowsy driver monitors system using perclos, Contr. Autom.2005.

10. Giusti, C. Zocchi, and A. Rovetta, “A noninvasive system for evaluating driver vigilance level examining both physiological and mechanical data,” Intelligent Transportation Systems, IEEE Transactions March 2009.

