Drowsiness Detection based on EEG Signal analysis using EMD and trained Neural Network

Rupinder Kaur[1], Karamjeet Singh[2]

[1]Department of Electronics and Communication Engineering,
Baba Banda Singh Bahadur Engineering College, Fatehgarh Sahib, Punjab, India

[2]Assistant Professor, Department of Electronics and Communication Engineering,
Baba Banda Singh Bahadur Engineering College, Fatehgarh Sahib, Punjab, India

Abstract: ***Detection of drowsiness based on extraction of IMF's from EEG signal using EMD process and characterizing the features using trained Artificial Neural Network (ANN) is introduced in this paper. Our subjects are 8 volunteers who have not slept for last 24 hour due to travelling. EEG signal was recorded when the subject is sitting on a chair facing video camera and are obliged to see camera only. ANN is trained using a utility made in Matlab to mark the EEG data for drowsy state and awaked state and then extract IMF's of marked data using EMD to prepare feature inputs for Neural Network. Once the neural network is trained, IMFs of New subjects EEG Signals is given as input and ANN will give output in two different states i.e. 'drowsy' or 'awake'. The system is tested on 8 different subjects and it provided good results with more than 84.8% of correct detection of drowsy states.***

Keywords: Drowsiness, EMD, EEG Signal, Neural Network

1. Introduction

Drowsiness: Transition between awaken state and sleep during which one's abilities to analyse and observe is strongly reduced is termed as drowsiness. Most of the accidents are the direct result of drowsiness of the person driving the car. It would thus be beneficial to be able to warn the driver in time by finding a way to detect drowsiness before it occurs. That is why more and more researches are made in this area to build automatic detectors of this dangerous state. Drowsiness detection researches have been done on some physiological indicators. The most important indicators are biomedical signals such as: electroencephalography (EEG), electrooculography (EOG), electrocardiograph (ECG) and electromyography (EMG). In some studies, researchers gave attention to video and image processing; they have used driver's eye and face videos for drowsiness detection. Ueno and his team [1] made a system that uses image processing technology and drowsiness is detected on the basis of the degree to which the driver's eyes are open or closed. Drowsiness detection on the basis of analysis of eyelid movement was introduced by Boverie et al., [2] in 1998. Wavelet method was used by Abdulhamit Subasi [3] in 2005, in which he extracted some statistical features from wavelet sub bands and for classification he used artificial neural networks. Another paper based on decomposing EEG signal to sub bands by wavelet transform and then extracted Shannon entropy of each sub bands. Dynamic clustering method was introduced in 2008, based on EEG to estimate vigilance states and used temporal series information to supervise EEG data clustering [4]. Wavelet transform for decomposition of EEG signal to its sub bands was used by Kurt et al. [5] and for increasing the accuracy of diagnosing the transition from wakefulness to sleep, they applied EEG sub bands and chine EMG and also left and right EOG to artificial neural network. Electrooculogram (EOG), to measure electrical muscles activity of the eye, has been widely used in the literature to estimate drowsiness ([2], [6]). EOG is the most reliable technique to detect and characterize blinks due to its high sample rate (from 250Hz to 500Hz) and is used as a reference to evaluate drowsiness by expert doctors ([7], [8]). EOG signal can be replaced by a high frame rate video (200fps) for the extraction of several blink features with the same accuracy as shown in a study by Picot et al. [9]. The database is first used to select the most relevant blinking features. A drowsiness detection method based on extraction of IMF's from EEG signal using EMD and using Artificial Neural network to characterize its features is then proposed and validated on the database.

Driving State: In this study, we have used a different protocol for data acquisition to simulate driving condition. Researchers have not given attention to driving situation in some previous researches. Some of them have recorded EEG signal from drowsy subjects in usual condition, but not while driving ([3], [5], [6], [10]). The best way for data recording from drowsy drivers, is when subjects drive a real car [11] but it is really expensive in terms of life and financial aspects as can cause dangerous events, which we are trying to avoid in all these researches. Further it makes the subjects stressful as he know that it is possible to get drowsy and have driving events, so it will be quite difficult for the subject to get into that state and is also a time consuming process. The EEG data recorded in this protocol will be a mixture of stress and drowsiness. But in real life, drivers that get drowsy are not aware of their drowsiness, so they have no stress or anxiety about incidence of accident before driving events.

So in our study, we have simulated driving condition by a simple method which was safe and simple; in our method, those subjects were selected which have travelled for last 8-10 hours and have not slept from last 24 hours. These subjects were to sit on chair in our study room facing Video EEG camera and are directed to see the camera only. In this way subjects were relaxed and they were not under stress and further they will get drowsy in a short span; so EEG signals will arise easily from drowsiness without any stress. After data acquisition, we have computed algorithm to convert Video EEG data into Matlab format. Then we have marked Drowsiness samples manually to train the Artificial Neural Network with two features i.e. drowsy and awake, using IMF's extracted from EEG signal using EMD. Now the trained ANN is ready to detect drowsy and awake state and when we pass new IMF extracted from EEG signal it will give output whether the passed IMF is matching to a drowsy state or awaken state.

2. Materials and Methods

2.1 Subjects

Eight volunteers participated and helped us taking EEG recordings for our study. The group consisted of males with a mean age of 26 years. They were obliged to be sleep deprived at least 24 hours before the data recording and took no medicine at least three days before the test. These subjects were selected on the basis of their job routine. They used to travel long distance due to their field jobs. When they came back from their field work back into office, then it was the right time to take the recordings as they were sleep deprived due to travelling whole night. It should be mentioned that all the subjects were selected from people who accepted and fulfilled all the obligations.

2.2 Equipments

In this study, we used portable EEG equipment, BrainTech 40+ with 24 channels and having sampling rate of 256 Hz provided by Clarity medical Pvt. Ltd., a medical equipment manufacturing company. We needed long time recordings of EEG data, so we had to use silver surface electrodes that were fixed on subject's scalp. In order to increase the connection between electrodes and scalp surface, special conductive EEG Paste was used. Electrode Placements of recorded EEG channels have been shown in Figure 1.

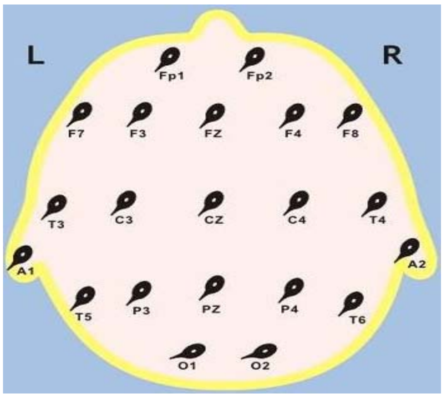


Figure 1: Electrode Placement

EEG is the spontaneous activity along the scalp. EEG signals are measured by placing several electrodes on the head around the brain. Between certain electrodes, a potential difference is measured and converted into a waveform (EEG signal). We have selected Bipolar Longitudinal Montage to record EEG signals. At the defined Bipolar Longitudinal montage for EEG equipment electrodes are placed according to a standard system known as the 10-20 system [14].

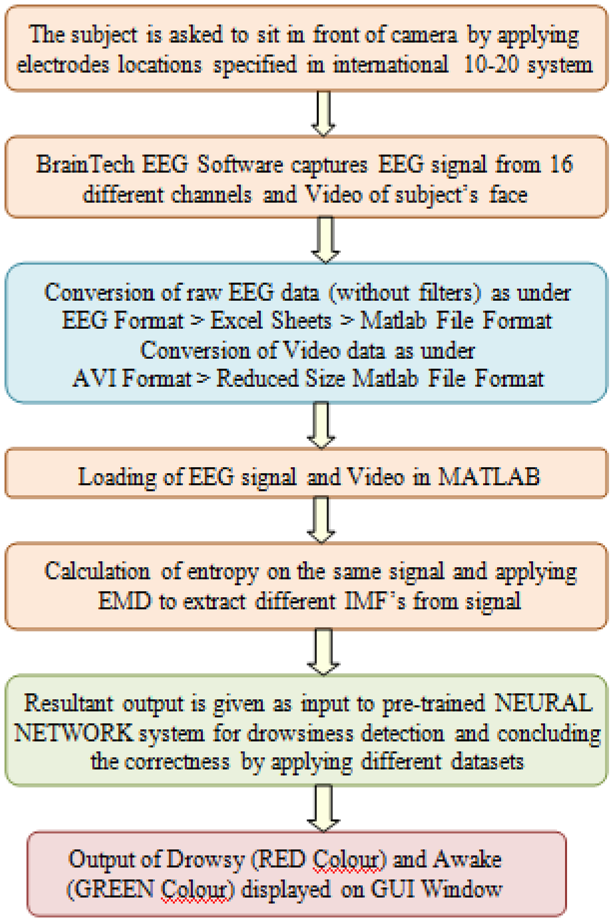
Table 1: List of Channels used and respective Montages

Sr. No.	*Channel*	*Montage*	*Sr.No.*	*Channel*	*Montage*
1	FP1	FP2 - F4	9	C4	FP1 - F3
2	FP2	F4 - C4	10	T4	F3 - C3
3	F7	C4 - P4	11	T5	C3 - P3
4	F3	P4 - O2	12	P3	P3 - O1
5	F4	FP2 - F8	13	P4	FP1 - F7
6	F8	F8 - T4	14	T6	F7 - T3
7	T3	T4 - T6	15	O1	T3 - T5
8	C3	T6 - O2	16	O2	T5 - O1

Each electrode is linked to the next along a chain from left to right across the head for reaching the pure signal of each channel. Finally, we have used 16 channels listed in Table 1 for our study purpose.

2.3 Drowsiness Detection Steps

Steps used in our study are shown in the flowchart given below



In the first step, EEG recording is taken from the subject using BrainTech EEG Hardware and acquisition software by placing electrode on the scalp. The synchronized video is also taken from the camera placed in front of subject using same BrainTech software. Standard settings for the HPF (High Pass Filter) and a LPF (Low Pass Filter) i.e. 1 Hz and 70 Hz are set respectively. An additional notch filter is typically used to remove artifact caused by electrical power lines (50 Hz). Since an EEG voltage signal represents a difference between the voltages at two electrodes, the representation of the EEG channels is referred to as a montage. In our recordings we used Bipolar Transverse Montage which shows better results for Drowsy and Sleep Stage in terms of Frequency changes producing Alpha and Theta Bands. After recording, EEG data is analyzed using BrainTech Analysis Software provided by Clarity Medical. The EEG data and Video is saved in .eeg format and .avi format. To use EEG data in our Matlab application we need this data without software filter implementation in Excel Format, so this data was converted from .eeg format to .xls format using a converter tool provided by Clarity. Now the final output is EEG raw data in Excel file having data of 10 Seconds of each channel on every sheets and a video file in .avi format. In next step this EEG data is converted into the Matlab data files using a utility designed in Matlab.

EEG Data Analysis: After EEG Recording, drowsiness positions are marked using a utility designed in Matlab which will show video of the subject. The video frames numbers are noted in excel for drowsy positions. These frame numbers are used as input to train the Neural Network. 20 samples from each channel are fetched from the marked locations for Drowsy and Awake positions and EMD is applied to extract different IMF's. The Empirical Mode Decomposition method (EMD for short), which was introduced by Dr. Norden Huang ([12], [13]), is an effective tool for adaptive local time–frequency decomposition is used to obtain the intrinsic mode functions (IMFs) from the EEG signal. To be considered as an IMF, a signal must satisfy two conditions:

1. The number of extrema's and the number of zero crossing must be equal or differ at most by one.
2. The mean value of the upper and lower envelope is zero everywhere.

EMD algorithm can be described as:

1. Generate $x^i[n] = x[n] + w^i[n]$, where $w^i[n]$ (i =1,…,I) are different realizations of white Gaussian noise
2. Each $x^i[n]$ (i = 1,…,I) is fully decomposed by EMD getting their modes $IMF^i_k[n]$, where k = 1,...,K indicates the modes
3. Assign IMF_k as the k-th mode of x[n], obtained as the average of the corresponding IMFik (1):

$$IMFk[n] = 1/I \sum^{I}_{i=1} IMF^i_k[n] \quad (1)$$

The different Frequencies extracted from EEG signals using EMD are shown in figure 2.

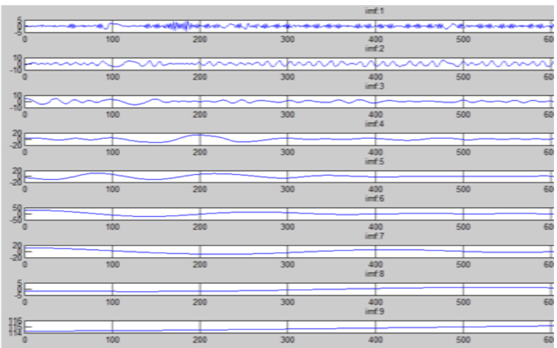


Figure 2: IMF's extracted using EMD

Neural Network Training: After the individual IMFs are found by EMD, their instantaneous frequencies are typically obtained via the Hilbert transform. In this way two type of Input Features i.e. drowsy and Awake are made to train the neural network. As we know the sample inputs, the respective outputs are also made for the neural network for training purpose. While training the neural network 70% samples are used for training, 15% samples are used for testing and remaining 15% samples are used for validation. As the neural network is ready for drowsiness detection, it is tested for remaining 7 subjects EEG data recording. Now IMF's of EEG recording are given as input to the trained network and it gives two outputs after matching the input with its database.

3. Results and Discussions

There are many algorithms available for Drowsiness Detection. But as EEG-based method can use a shorter moving-averaged window to track second-to-second fluctuations in the subject performance, a new algorithm for drowsiness detection using EEG signal is proposed. This algorithm was implemented by using MATLAB software. We have written a separate code for each step of algorithm independently. In this study, we have tried to introduce a very simple method for EEG data collection from drowsy subjects. The situation was made similar to a real driving situation where a driver is sleep deprived and constantly watching the road while driving. Here in our setup the subject is sitting on chair facing camera and is advised to see the camera only. As discussed earlier the subject is sleep deprived due to his routine field job work so he achieves drowsiness in a short span. After EEG recording and video signals recording synchronously, we did some pre-processing on datasets, to make it work on Matlab. Manual labeling was done on all the records using Take Sample Utility designed to note down the drowsy state Video frames. To extract Feature from recorded signals, we have generated IMF's of EEG signal by applying EMD. Extracted Features are used to train the Neural Network. The neural network was trained up to 83.6 % accuracy level with 100 % validation results. The details of the confusion matrix of neural network training are shown in figure 3.

Figure 3: Confusion Matrix of Neural Network Training

Ability of extracted features in discriminating alertness and drowsiness has been evaluated by ANN classifier. The results have been shown in Tables 2.

Table 2: ANN drowsiness detection results

Subject No.	*Subject Code*	*Drowsiness Position Marked manually*	*ANN Detected*	*Accuracy %*
1	1234	41	34	82.93
2	1189	16	13	81.25
3	1187	40	39	97.50
4	1062	28	25	89.29
5	07	53	48	90.57
6	0005	45	40	88.89
7	0004	37	32	86.49
8	0002	63	56	88.89
Average Accuracy Level				88.22

Actually by using these features two states of features are distinct and it is possible to make drowsy drivers alert by an alarm, so this discrimination would be useful in accident preventing. Results of classification also show that accuracy of classification by these features is above 88%. This is an evident that drowsy driving detection by mentioned features is possible. Our new protocol would be a suitable and simple way for data collection in virtual driving condition.

4. Conclusion

A method to detect drowsiness based on EEG signal analysis using EMD and pre trained neural network has been presented here. The different features used in this system have been selected using a utility designed in Matlab manually on a consistent database. The Method has been tested on eight subjects and does not need to be tuned. Its validation on EEG signals gives good results with 88.2% of correct detections and only 11.8% of false alarms. The next step of this work is the achievement to train neural network more than 90 % as currently it is trained up to 83.6 %. Once trained up to that level, this EEG based drowsiness detection system should be able to achieve more than 95% good results and can be added to EEG based drowsiness detection system to obtain a highly reliable automatic drowsiness detector.

5. Acknowledgement

The authors are grateful to Clarity Medical for providing EEG Machine and helping in recording of EEG data in their premises.

.

References

[1] Ueno H, Kaneda M, Tsukino M. Development of drowsiness detection system. In Proc. of 1994 vehicle navigation and information systems Conference, Yokohama, Japan, IEEE 1994. p. 15-20.

[2] Boverie S, Leqellec JM, Hirl A. Intelligent systems for video monitoring of vehicle cockpit. In The 1998 international congress and exposition ITS: Advanced Controls and vehicle navigation systems. SAE international; SAE Technical Paper 980613, 1998, doi: 10.4271/980613, p. 1-5.

[3] Subasi A. Automatic recognition of alertness level from EEG by using neural Network and wavelet coefficients. Expert Syst App 2005; 28:701-11.

[4] Li-Chen Shi, Bao-Liang Lu. Dynamic Clustering for Vigilance Analysis Based on EEG. 30th Annual International IEEE EMBS Conference Vancouver, British Columbia, Canada, August 20-24, 2008.

[5] Kurt MB, Sezgin N, Akin M, Kirbas G, Bayram M. The ANN-based computing of drowsy level. Expert Syst Appl 2009; 36:2534-42.

[6] Vuckovic A, Radivojevic V, Chen AC, Popovic D. Automatic re cognition of alertness and drowsiness from EEG by an artificial neural network. Med Eng Phys 2002; 24:349-60.

[7] Lin CT, Chen YC, Wu RC, Liang SF, Huang TY. Assessment of Driver's Driving Performance and Alertness Using EEG-based Fuzzy Neural Networks, ISCAS 2005. IEEE International Symposium on Circuits and Systems, Vol. 1. 2005. p. 152-5.

[8] Byung-Chan Chang, Jung-Eun Lim, Hae-Jin Kim, Bo-Hyeok Seo. A study of classification of the level of sleepiness for the drowsy driving prevention. SICE Annual Conference 2007, Kagawa University, Japan, Sept. 17-20, 2007.

[9] Hu Shuyan, Zheng Gangtie. Driver drowsiness detection with eyelid related parameters by Support Vector Machine. Expert Systems with Applications.

[10] Yildiz A, Akin M, Poyraz M, Kirbas G. Application of adaptive neurofuzzy inference system for vigilance level estimation by using waveletentropy feature extraction. Expert Syst Appl 2008; Vol. 36 Issue 4:P. 7390-7399.

[11] Papadelis C, Kourtidou-Papadeli C, Bamidis PD, Chouvarda I. Indicators of Sleepiness in an ambulatory EEG study of night driving in Proc. of the 28th IEEE EMBS Annual International Conference New York City, USA, Aug 30-Sept 3, 2006.

[12] N.E. Huang et al., "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis," Proc. R. Soc. Lond. A, vol. 454, pp.903–995, 1998.
[13] Z. Wu and N. E. Huang, "Ensemble empirical mode decomposition: A noise-assisted data analysis method," Advances in Adaptive Data Analysis, vol. 1, no. 1, pp. 1–41, 2009.
[14] Ernst Niedermeyer, Fernando Lopes da Silva, Electroencephalography: Basic Principles, Clinical Applications, and Related Fields - Page 140, Lippincott Williams & Wilkins, 2004 ISBN 0-7817-5126-8, ISBN 978-0-7817-5126-1.

Author Profile

Rupinder Kaur completed B. Tech degree in Electronics and Communication from GGS College of Modern Technology in 2007. I worked as Lecturer (ECE) in GGS Polytechnic College from 2007-09. I am doing part-time M.Tech degree from BBSB Engineering College and also working as Lecturer (ECE) in Doaba Engineering College since 2009.

Karamjeet Singh is working with Baba Banda Singh Bahadur Engineering College in department of Electronics and Communication as an Assistant Professor since 2009. He did his B. Tech degree from IITT College of Engineering, Pojewal and M. Tech degree from Panjab University, Chandigarh in Electronics and Communication.