PNN BASED DRIVER DROWSINESS LEVEL CLASSIFICATION USING EEG

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ABSTRACT

In this work, we classify the driver drowsiness level (awake, drowsy, high drowsy and sleep stage1) based on different wavelets and probabilistic neural network classifier using wireless EEG signals. Deriving the amplitude spectrum of four different frequency bands delta, theta, alpha, and beta of EEG signals. Comparing the results of PNN based on spectral centroid, and power spectral density features extracted by different wavelets (db4, db8, sym8, and coif5) from the amplitude spectrum of the said bands. As results of this study indicates that the best average accuracy achieved of 61.16% based on power spectral density feature extracted by db4 wavelet.

Keywords: *Discrete Wavelet Transform, EEG, Fast Fourier Transform, probabilistic neural network.*

1. INTRODUCTION

In general, 20% of all road accidents are mainly due to driver drowsiness [1-3]. Drowsiness can be detected by electroencephalographic (EEG) recording, or vehicle behaviour and driver physical response (head position, eye blinking and movement)[4]. In this work The Electroencephalography is used because it the most technique applied to measure the electrical activity of the brain [5]. Subasi [6] achieved a 92% discrimination rate between alert, drowsy and sleep based on extraction wavelet coefficients from the frequencies of alpha, delta, theta, beta bands. Tsai et al. [7] design a real time system which can discriminate alertness from drowsiness with accuracy 79.1% and 90.91% respectively. Torbjorn et al. [8] used EEG, EOG, and EMG to identify sleep stages (1, 2, 3, 4). This work has two objectives: (1) to determine the best feature for classifying the drowsiness levels under PNN (2) to select the optimal wavelet function for getting the better classification accuracy. Two features (spectral centroid (SC), and power spectral density (PSD)) are derived using wavelet transforms by applying different wavelet functions ("db4", "db8", "sym8", and "coif5") on the said frequency bands.

The rest of this paper is organized as follows. In Section II, we summarize the research methodology by elucidating the data acquisition process, pre-processing, feature extraction using wavelet transform, and classification of sleepy levels by PNN classifier. Section III illustrates the overview of the results and discussion of this present work, and finally conclusions are given in Section IV

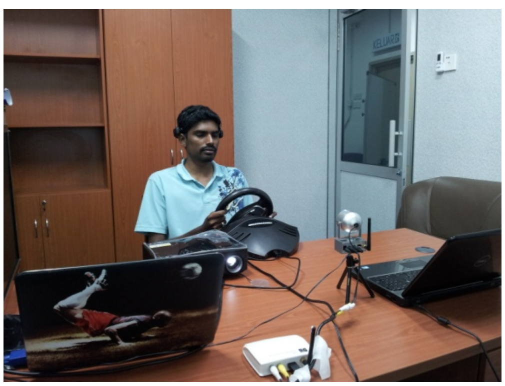
2. DATA ACQUISITION

Figure 1. shows a simulated environment of real driving in one of our university laboratory based on simulation driving software. Infrared camera had been used to capture the driver face image for data validation after finishing the experiment.

Before start driving, the subject asked to initially keep eyes closed for 2 min duration followed by another two minutes for open eyes. After this neutral initialization, the driver asked to drive for 1 hour under soft music. Through this protocol and according to the visually inspection for 50 subjects, we allocate the subject drowsiness for less than 3 sec. as drowsy state which still under driver control, but if it exceed 3 sec., then it considered as high drowsy case which mean the driver in dangerous situation because this period is enough to make accident. However after 10 minutes of sleeping, the subject considered in sleep stage 1 [9]. In this work, 50 subjects (43 Males and 7 Females) in the age range of 24 years to 34 years have participated. Emotive EEG System is used to acquire the EEG signals over the complete scalp through 14 electrodes (FP1, FP2, F7, F8, F3, F4, T7, T8, P7, P8, O1, O2, A1, &A2). All the electrodes are placed over the subject scalp based on International

10-20 system of electrode placement. EEG signals are acquired at a sampling frequency of 128 Hz and band pass filtered between 0.05 Hz and 60 Hz. The reference electrode and ground electrode are placed on right and left ear lobes. The impedance of the electrodes is kept below 5 KΩ.

(a)



(a)

Figure 1. Protocol Flow (A) Driving Car Environment (B) Subject In Drowsy State

FEATURE EXTRACTION

Discrete Wavelet Packet Transform (DWPT) and plays a vital role in localizing the frequency bands compared to other methods [10]. In this work, the spectrum features from the EEG signals for different drowsiness levels are derived from four frequency bands, namely delta, theta, alpha and beta. In general, the characteristic nature of mother wavelet function should be similar in shape to the original signal under processing. The mother wavelet function (Ψ) can be expressed as given in Eqn. (1).

$$\Psi_{b,a}(t) = \frac{1}{\sqrt{|b|}}\Psi\left[\frac{t-a}{b}\right] \quad a,b \in R,\ b \neq 0 \qquad (1)$$

where a, b ∈ R, a>0, and R is the wavelet space. Parameter 'b' is the scaling factor and ‘a’ is the shifting factor. The time-frequency representation is performed by consequently filtering the input signal of each level with a low pass and high pass filters as shown in Figure 2. These filters separate the input signal frequency into two equally spaced bandwidth parts, the output of lower frequency band is called as approximation coefficients, and the upper frequency band coefficients are called as details coefficients. DWPT produces four frequency bands, namely delta (0-4Hz), theta (4-8Hz), alpha (8-12Hz), and beta (14-32Hz) frequency bands for drowsiness classification as shown in table (1).

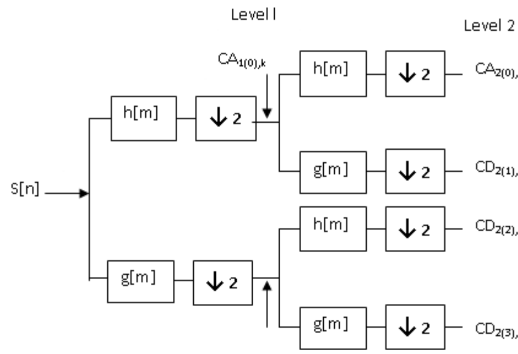


Figure 2. Block Diagram Shows The DWT Decomposition

Table 1: EEG Band Level And Its Bandwidth Used For Drowsiness Detection

Frequency Range (Hz)	Decomposition level	EEG Band	Bandwidth(Hz)
0-4	WPT 4-0	delta	4
4-8	WPT 4-1	Theta	4
8-12	WPT 4-2	Alpha	4
14-16	WPT 5-7	Beta1	2
16-32	WPT 2-1	Beta2	16

In this work, we considered db4, db8, sym8, and coif5 wavelet functions for extracting the spectrum features from the EEG signals. Since, theses said wavelets waveform is similar to that to be extracted from the EEG signal.

In this work, the average amplitude of the FFT output of EEG bands wavelet transformed is used to derive two different features namely; spectral centroid, and PSD. Spectral analysis is the distribution of power over frequency. A random signal usually has finite average power and, therefore, can be characterized by an average power spectral density as in Eqn. (2).

$$PSD(i) = \sum_{i=0}^{N} |X(k)|^2 \quad (2)$$

Where X(k) represent the out and k is the nuber of FFT components

The Spectral Centroid is used to find the center value of the groups for each frequency bands The Spectral Centroid is calculated using formula in Eqn. (3)

$$SC = \frac{\int kX(k)dk}{\int X(k)dk} \quad (3)$$

3. PNN CLASSIFIER

In this work, PNN architecture is constructed using newpnn () function in MATLAB 7.0. The PNN model is one among the supervised learning networks and has many features different from those of other networks in the learning processes. The data training set used to train designed PNN. The PNN is tested with testing data set to show the impact on classification rate. The probability for input X belonging to class A is given by the probability density function F_A.

$$F_A(x) = \frac{1}{N_k} \sum_{j=1}^{N_k} \exp\left(- \frac{\|x - x_{kj}\|}{2\sigma^2} \right) \quad (4)$$

Where X is the m dimensional input pattern vector, j is the pattern number, X_j is the jth training pattern for class A, N is the number of training patterns, and σ is an adjustable smoothing parameter. The classifier accuracy is examined with different values of σ. The first step of training the PNN network is by selecting the σ values which control the spread of the probability functions. If the σ is too large, then the model will not be able to closely fit the function, if the σ is too small, the model will over fit the data because each training point will have too much influence. In this work smoothing factor of 0.1 value been used to classify the hypo-vigilance level.

The requirement of generating classifier system is to divide the tanning data into two data sets. Firstly, an input data set which has 8 values of two features F1, F2 over four bands (δ,θ, α, β) [$F_{1,\delta}$ $F_{1,\theta}$ $F_{1,\alpha}$ $F_{1,\beta}$ $F_{2,\delta}$ $F_{2,\theta}$ $F_{2,\alpha}$ $F_{2,\beta}$], where F1, F2 represent centroid frequency, and power spectral density features respectively. Hence each vector of the overall 200 vectors is contain 8 values. Therefore the overall data input are 1600 values over 50 subjects for four levels (50 *4*8). Secondly, an output data set (1, 2, 3, or 4) is used for one output. The output either 1 for neutral or 2 for drowsy, or 3 for high drowsy, and 4 for sleep1. These points were placed into a single output data set with 200 values, each 50 values for one class. Where 60% of the vectors used as training (120) and 40% as testing (80).

4. RESULTS AND DISCUSSION

This research work is to analyze the effects of drowsiness due to long monotonous driving task at the late night or in the afternoon.

From table (2), although sym8 produce highest accuracy of 82.05% in discriminating awake state from the other states, we concluded that db4 wavelet is most suitable wavelet for drowsiness classification because it achieves maximum classification of 61.16% using PSD feature which its input vectors distribution is shown in Figure 3. Therefore, we considered this wavelet for subsequent analysis. The parameters, namely; accuracy, sensitivity, specificity, true positive rate (TPR), and false negative rate (FNR) are commonly used as performance measures of classification tests. Sensitivity is the proportion of actual positives which are correctly identified as positive, and specificity is the Proportion of negatives which are correctly identified as negative.

Table (3) summarizes these parameters for the two features (SC, PSD) under db4. The best performance of classification of 75.85% was achieved by PNN using PSD feature with an average sensitivity of 79.35%, specificity of 68.02%, TPR of 71.42 %, and FNR of 64.24% in discriminating awake state from other levels under this db4 wavelet. Moreover, the best overall average accuracy of 61.16% , sensitivity of 64.22%, specificity of 55.05 %, TPR of 57.80%, and FNR of 51.99% based on PSD feature. Therefore, db4 wavelet can be considered as the dominant wavelet type for get good accuracy of classification of different levels of distraction based on PSD feature.

Table 2: Classification Accuracy Of Different Driver Drowsiness Level Using Four Different Wavelets

Wavelet	awake		drowsy		high drowsy		sleep1		Avg.	
	SC	PSD	SC	PSD	SC	PSD	SC	PSD	SC	PSD
db4	64.98	75.58	72.93	58.13	40.52	58.41	44.52	*52.54*	53.24	61.16
db8	68.31	60.76	65.85	44.63	71.40	72.35	56.85	*58.03*	60.60	51.44
sym8	66.54	82.05	66.89	54.06	61.58	61.16	55.96	*51.08*	57.74	59.59
coif5	62.64	63.51	68.12	34.57	70.22	62.95	55.15	*45.73*	59.03	49.19

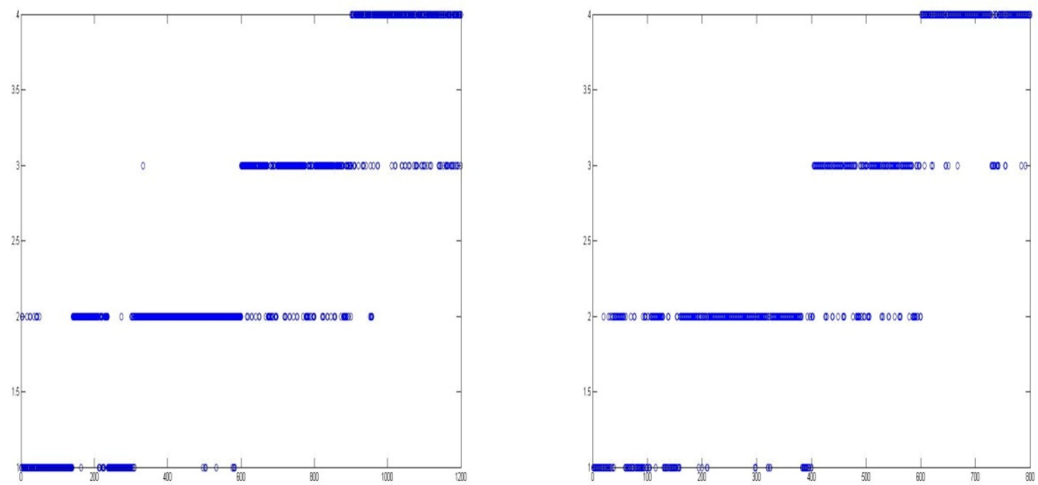


Figure 3. The Distribution Of The Input Vectors To The Fuzzy Classifier Over 4 Distraction Levels Based On Fuzzy Classifier (A) 120 Training (B) 80 Testing Vectors

Table 3: Performance Of Drowsiness Levels Classification Based On "Db4" Wavelet Function Using Spectral Centriod And PSD Features

State	Features	% CR	SEN.	SPEC.	TPR	FNR
Neutral (awake)	SC	64.98	68.23	58.49	61.41	55.24
	PSD	75.58	79.35	68.02	71.42	64.24
drowsy	SC	72.93	76.58	65.64	68.92	61.99
	PSD	58.13	61.04	52.32	54.93	49.41
High drowsy	SC	40.52	42.54	36.46	38.29	34.44
	PSD	58.41	61.33	52.57	55.19	49.65
Sleep 1	SC	44.52	46.25	41.07	42.62	49.34
	PSD	*52.54*	55.17	47.29	49.65	44.66
Avg.	SC	53.24	55.90	47.91	50.31	45.25
	PSD	61.16	64.22	55.05	57.80	51.99

5. CONCUSION

Most of the research works have discussed about the classification of driver drowsiness into two levels (drowsy or awake) based on EEG frequency bands. This paper presents amplitude spectrum of the four bands (delta, theta, alpha, and beta) of the EEG signal based on DWPT for extraction centroid, and PSD features. The proposed methodology has been tested on 50 subjects and provides maximum accuracy of 61.16% using db4 and PNN for PSD feature with an average sensitivity of 64.22% and specify of 55.05%.

REFRENCES:

[1] Lyznicki M.J., Doege C.T., Davis M.R., Williams A.W., "Sleepiness, driving, and motor vehicle crashes," JAMA, 279(23):1908-1913, 1998.

[2] Horne A.J., Reyner A.L., "Sleep-related vehicle accidents," British Medical Journal, 310:565-567, 1995.

[3] McCartt T.A., Ribner A.S., Pack A.I., Hammer C.M., "The scope and nature of the drowsy driving problem in New Youk State, " Accident Analysis and Prevention, 28 (4):511-517, 1996.

[4] Hayami T. , Matsunaga K., Shidoji K., Matsuki Y., "Detecting Drowsiness While Driving by Measuring Eye Movement-A Pilot Study," in Proc. 5th Internation Conference on Intelligent Transportation Systems, Singapore, 2002, pp. 156-161.

[5] HamadaT., Adachi K., Nakano T., Yamamoto S., "Detecting Method for Drivers' Drowsiness Applicabel to Individual Features," In Proc. 2003 Intelligent Transportation Systems, Vol. 2, 2003, pp 1405-1410.

[6] Subasi A., "Automatic recognition of alertness level from EEG by using neural network and wavelet coefficients,"Expert Systems with Applications, 28, pp. 701–711, 2005.

[7] Tsai P., Weichih H., Kuo B.J., Shyu L., "A Portable Device for Real Time Drowsiness Detection Using Novel Active Dry Electrode System," In Proc. 2009 International Conference of the IEEE EMBS Minneapolis, Minnesota, USA, 2009, September 2-6.

[8] Torbjorn A., Peter M., Kecklund G., " Sleep and Recovery" Current Perspectives on Job-Stress Recovery Research in Occupational Stress and Well Being, by Emerald Group Volume 7, 2009, 205–247.

[9] Carskadon, MA, Dement WC, Monitoring and staging human sleep. In M.H. Kryger, T. Roth, & W.C. Dement (Eds.), *Principles and practice of sleep medicine*, 5th edition, (pp 16-26). St. Louis: Elsevier Saunders, 2011.

[10] Murugappan M., Nagarajan R., Yaacob S., "Comparison of Different Wavelet Features fromEEG Signals for Classifying Human Emotions", IEEE Symposium on Industrial Electronics and Applications Kuala Lumpur, Malaysia, October 4-6, 2009.