

Subtractive Fuzzy Classifier Based Driver Distraction Levels Classification Using EEG

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Abstract. [Purpose] In earlier studies of driver distraction, researchers classified distraction into two levels (not distracted, and distracted). This study classified four levels of distraction (neutral, low, medium, high). [Subjects and Methods] Fifty Asian subjects (n=50, 43 males, 7 females), age range 20–35 years, who were free from any disease, participated in this study. Wireless EEG signals were recorded by 14 electrodes during four types of distraction stimuli (Global Position Systems (GPS), music player, short message service (SMS), and mental tasks). We derived the amplitude spectrum of three different frequency bands, theta, alpha, and beta of EEG. Then, based on fusion of discrete wavelet packet transforms and fast fourier transform yield, we extracted two features (power spectral density, spectral centroid frequency) of different wavelets (db4, db8, sym8, and coif5). Mean \pm SD was calculated and analysis of variance (ANOVA) was performed. A fuzzy inference system classifier was applied to different wavelets using the two extracted features. [Results] The results indicate that the two features of sym8 possess highly significant discrimination across the four levels of distraction, and the best average accuracy achieved by the subtractive fuzzy classifier was 79.21% using the power spectral density feature extracted using the sym8 wavelet. [Conclusion] These findings suggest that EEG signals can be used to monitor distraction level intensity in order to alert drivers to high levels of distraction.

Key words: Discrete wavelet transform, EEG, Fuzzy inference system

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INTRODUCTION

Distraction is considered as the main reason for many car accidents. EEG plays a vital role in measuring the electrical activity of the brain¹⁾. Different signal processing techniques, like wavelet transforms²⁾, means comparison test³⁾, independent component analysis⁴⁾ with different classifiers such as neural networks^{5–7)}, and fuzzy logic⁸⁾, have been used to detect distraction and drowsiness in EEG signals. Driving is a complex task in which different skills and functions are combined simultaneously, therefore monitoring drivers attention regarding brain resources is a demanding challenge for researchers in the field of cognitive brain research and brain-computer interface. Causes of distractions during driving are quite widespread, and include eating, drinking, talking with passengers, use of cell phones, reading, fatigue, problem solving, and using in-car equipment such as GPS, media players and in-vehicle entertainment, thus making driver inattention a likely problem^{9, 10)}. Many researchers have proposed methods for detecting attention distraction using physiological changes such as eye blinking, heart rate, pulse rate, skin electric potential, and brain waves^{11, 12)}. The main objective of this work was to select the optimal wavelet functions and features of the alpha,

theta, and beta EEGs which give better accuracy in classification of the driver distraction into four levels.

SUBJECTS AND METHODS

The main causes of driver distraction are mobile phones, GPS, music and video players, and mental thinking. Therefore, we used these four distractions to develop a suitable database for the study of EEG signals. A simulated environment of real driving at our university laboratory was created using simulation driving software. An infrared camera was used to capture drivers' face images for data validation after completion the experiment.

The subjects were asked to drive for 30 minutes during which different distraction tasks, each of 2 minutes duration, such as using a media player, GPS, mental activity induced by answering a few questions asked by mobile phone, and finally typing and sending SMS messages. Through this protocol and according to the continuous performance test (CPT), we can determine whether subjects were in low, medium, or high levels of distraction according to their time responses in scanning

the screen and controlling the steering wheel. First, we visually determined the one-second duration of distraction which we considered as low level. Then, for the medium level, a continuous two-second distraction time was extracted. A continuous three-second distraction time was considered

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to be a high level. Fifty subjects (43 males and 7 females) in the age range of 24 years to 34 years participated in this study. The Emotive EEG System was 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 were placed on the subjects' scalps using the International 10–20 system of electrode placement. EEG signals were acquired at a sampling frequency of 128 Hz and band pass filtered between 0.05 Hz and 60 Hz. The reference electrode and ground electrodes were placed on the right and left ear lobes. The impedance of the electrodes was kept below 5 KΩ.

In this work, the spectral features of the EEG signals of the different distraction levels were derived for three EEG frequency bands, namely, theta, alpha and beta, by applying four different wavelets (db4, db8, sym8, and coif5). The waveforms of these wavelets are similar to waveforms in the EEG signal. We used discrete wavelet packet transforms (DWPT) for efficient frequency band localization. DWPT decomposes both the high and low frequency components of the input signal into any level of decomposition unlike normal wavelet transforms which decompose only the approximation coefficients in the subsequent levels. In this work, DWPT was used to process three frequency bands, namely theta (4–8Hz), alpha (8–12Hz), and beta (14–32Hz) frequency bands to identify distraction levels as shown in Fig. 1.

In this work, the average amplitudes of the fast Fourier transform FFT output of wavelet-transformed EEG bands were used to derive two different features namely; the spectral centroid (SC), and power spectral density (PSD).

Spectral analysis examines the distribution of power across frequency. In medicine, spectral analysis of various signals, such as electrocardiograms or electroencephalograms signals can provide useful material for diagnosis. A random signal usually has finite average power and, therefore, can be characterized by an average power spectral density as in Equation (1).

$$PSD(i) = \sum_{i=0}^N |X(k)|^2 \quad (1)$$

Spectral centroid frequency is commonly known as sub band spectral centroid. The spectral centroid is used to find the center value of the groups of each frequency bands. In this work, the authors used this feature for EEG classification. The spectral centroid is calculated using the formula in Equation (2).

$$SC = \frac{\int kX(k)dk}{\int X(k)dk} \quad (2)$$

Fuzzy subtractive (FS) clustering is a fast, one-pass algorithm for estimating the number of clusters and the cluster centers in a set of data. This technique depend upon the measure of the density of data points in the feature space. The aim is to find areas in the feature space with high densities of data points. The point with the highest number of neighbors is considered to be the center of a specific clus-

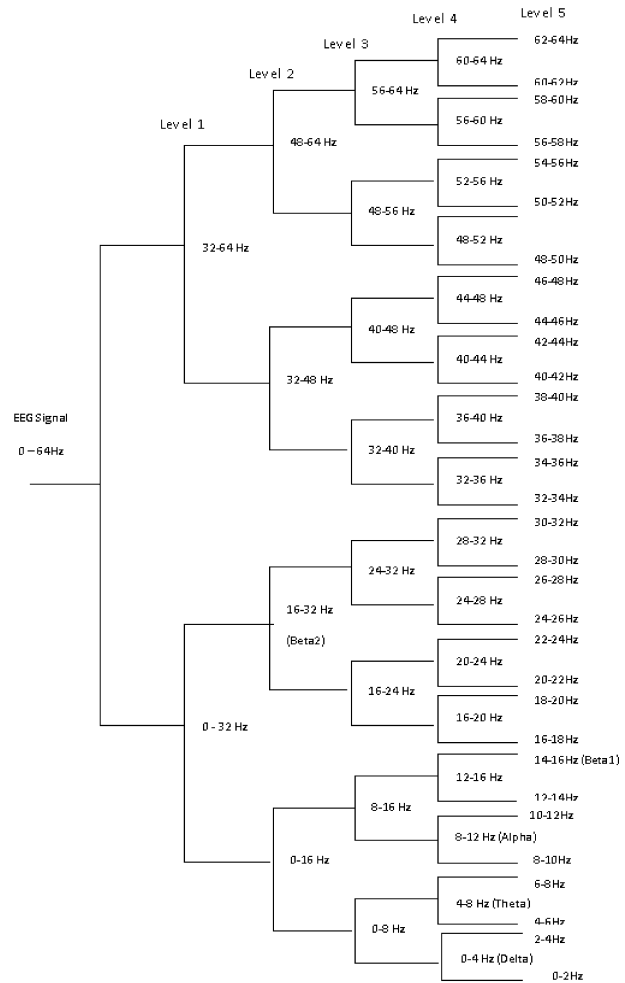


Fig. 1. Five level EEG signal decomposition using Discrete Wavelet Packet Transform (DWPT)

ter. The algorithm will remove data points within a pre-specified fuzzy radius. This process will check all the data points. The radii variable is a vector of entries between 0 and 1 that specifies a cluster center's range. Small radii values will generate a few large clusters. Recommended values for radii should be between 0.2 and 0.5. In this work, a value of 0.5 for all the radii was chosen, because this leads to fewer membership functions and less computation time, without losing accuracy. The Gaussian membership function selected since it has continuous derivability.

The function is given by $\mu(x) = e^{-\frac{(x-m)^2}{2\sigma^2}}$. This function has two factors, m and σ , and they represent the center and the width of the Gaussian function respectively. The requirement for generating a classifier system is to divide the training data into two data sets: an input data set which has 6 values of two features F1, F2 over three bands (θ, α, β) [F1, θ , F1, α , F1, β F2, θ , F2, α , F2, β], where F1, F2 represent centroid frequency, and power spectral density features, respectively. Hence, each vector of the overall 800 vectors has containing 6 values. Therefore, the overall data input is 4,800 values for 50 subjects at four levels of each stimulus

Table 1. ANOVA of SC and PSD features of db4, db8, sym8, and coif5 at each distraction level

Wavelet	Features	Neutral	Low	Medium	High
db4	SC	5.3 ± 50.8	15.5 ± 217.8	10.1 ± 239.8	9.3 ± 286.4
	PSD	0.41 ± 7.5	1.12 ± 18.8	0.013 ± 0.0007	0.019 ± 0.0039
db8	SC	1.29 ± 5.12	9.19 ± 113.9	4.6 ± 64.3	4.15 ± 53.8
	PSD	0.0008 ± 5.4E-06	6.78 ± 213.9	0.005 ± 0.0001	0.005 ± 0.0002
sym8	SC	1.26 ± 3.27	5.6 ± 49.6	5.4 ± 78.7	4.2 ± 61.7
	PSD	0.0008 ± 4.46E-06	2.3 ± 60.5	0.004 ± 8.6E-5	0.005 ± 0.0002
coif5	SC	2.02 ± 5.19	15.6 ± 395.4	10.7 ± 372.7	7.66 ± 199.9
	PSD	0.002 ± 0.00003	0.03 ± 0.003	0.048 ± 0.024	0.04 ± 0.02

Table 2. Classification accuracy of different classifiers for different wavelets across 4 distraction levels for both PSD and SC

Wavelet	Neutral		Low		Medium		High		Avg.	
	SC	PSD	SC	PSD	SC	PSD	SC	PSD	SC	PSD
db4	71.17	77.73	67.08	79.21	79.32	84.80	64.87	70.99	70.61	78.18
db8	64.17	73.24	77.29	89.90	75.99	71.73	63.61	79.41	70.27	78.57
sym8	62.51	72.79	82.61	91.99	81.01	70.60	63.65	79.21	72.45	79.21
coif5	65.36	74.94	63.19	66.30	76.81	78.22	62.68	63.55	67.01	70.75

(50 *4*4*6). Then, output data sets (1, 2, 3, or 4) are used for one output. The output is 1 for neutral, 2 for low level, 3 for medium level, and 4 for high level. These points were placed into a single output data set with 800 values, 200 values for each class, in which 60% of the vectors were used as training (480) and 40% as testing (320).

RESULTS AND DISCUSSION

This research work investigated the effects of distraction with cognitive, visual, and auditory stimuli using different stimuli. In this work, we localized the frequency bands of EEG signals through DWPT and FFT for efficient feature extraction to classify distraction. The significance of SC and PSD were checked using analysis of variance (ANOVA) for each wavelet (db4, db8, sym8, and coif5) (Table 1).

All the results are presented as mean ± SD with p values. The ANOVA test gave results with p values generally less than 0.005, suggesting that PSD and SC can be used for classification. We extracted PSD and SC features from the amplitude spectrum and performed the ANOVA test for the four classes of distraction (neutral, low, medium, and high). PSD and SC gave excellent p values in the ANOVA test (Table 1). They were computed from three-second windows of the 14 EEG channels, and the ANOVA test was used to check if the mean values were different among the different levels of distraction. Table 1 shows the results of the amplitude spectrum parameters for the different wavelets over the four levels of distraction. The mean SC and PSD magnitudes decreased from neutral to low to medium to high distraction, based on db4-processed EEG, with a maximum significance value of p<0.001. Therefore, both PSD and SC of db4 are suitable for differentiating and classifying distraction. For db8 PSD and SC did not differentiate between the medium and the high distraction

levels, showing no significant change. For sym8, the mean SC magnitude decreased from low to medium to high levels of distraction. Moreover, PSD and SC were very weak at medium distraction levels, and this means they contain fewer resources. Therefore, it should be easy to distinguish this state from low and high distraction levels, since the maximum significance value with p<0.001. For coif5, SC decreased from low to medium to high levels of distraction, while PSD showed almost no significant changes. Therefore, the sym8 wavelet is the most suitable wavelet for distraction classification, and it gave maximum classification accuracy of 79.10% (Table 2) using the PSD feature as a fuzzy classifier. Moreover, this wavelet gave the highest classification accuracy of 91.99% in discriminating the low level from the other levels of distraction. Therefore, we used this wavelet for further analysis. Sensitivity and specificity 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 the classification accuracy (% CR), sensitivity, specificity, true positive rate (TPR), false negative rate (FNR) of fuzzy classifier for the two features (SC, PSD) extracted using sym8. The highest classification rate of 91.99% was obtained in discriminating the low level from the other levels, and it had a sensitivity of 96.59%, specificity of 82.79%, TPR of 86.93%, and FNR of 78.19%. The overall classification accuracy was 79.21% with an average sensitivity of 83.17%, specificity of 71.29%, TPR of 74.86%, and FNR of 67.33%. Therefore, the sym8 wavelet can be considered as the dominant wavelet type for get good accuracy of classification of different levels of distraction based on its PSD feature.

Table 3. Classification results of fuzzy classifiers for the 4 distraction levels based on the SC & PSD features of sym8

Case	Features	% CR	SEN.	SPEC.	TPR	FNR
Neutral	SC	62.51	65.64	56.26	59.07	53.13
	PSD	72.79	76.43	65.51	68.79	61.87
Low	SC	82.61	86.74	74.35	78.07	70.22
	PSD	91.99	96.59	82.79	86.93	78.19
Medium	SC	81.01	85.06	72.91	76.55	68.85
	PSD	70.6	74.13	63.54	66.71	60.01
High	SC	63.65	66.83	57.29	60.15	54.1
	PSD	81.48	85.56	73.33	77	69.26
Average	SC	72.45	76.07	65.2	68.46	61.58
	PSD	79.21	83.17	71.29	74.86	67.33

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