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EEG-based Safety Driving Performance Estimation and Alertness Using Support Vector Machine

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Abstract

Safety driving performance estimation and alertness (SDPEA) has drawn the attention of researchers in preventing traffic accidents caused by drowsiness while driving. Psychophysiological measures, such as electroencephalogram (EEG), are accurately investigated to be robust candidates for drivers' drowsiness evaluation. This paper presents an effective EEG-based driver drowsiness monitoring system by analyzing the changes of brain activities in a simulator driving environment. The proposed SDPEA system can translate EEG signals into drowsiness level. Firstly, Independent component analysis (ICA) is performed on EEG data to remove artifacts. Then, eight EEG-band powers-related features: beta, alpha, theta, delta, (alpha plus theta)/beta, alpha / beta, (alpha plus theta)/(alpha plus beta) and theta / beta are extracted from the preprocessed EEG signals by employing the Fast Fourier Transform (FFT). Subsequently, fisher score technique selects the most descriptive features for further classification. Finally, Support Vector Machine (SVM) is employed as a classifier to distinguish drowsiness level. Experimental results show that the quantitative driving performance can be correctly estimated through analyzing driver's EEG signals by the SDPEA system.

Keywords: *Driving safety, EEG, independent component analysis, SVM*

1. Introduction

In recent decades, traffic accident continues to be one of the leading causes of death and injuries for individuals. Therefore safety driving performance estimation and alertness has received increasing attention of the publics [1]. As is widely assumed, fatigue or drowsiness has been considered as one of the most important contributors to traffic accidents because of the marked decline in the drivers' abilities of perception, recognition and vehicle control abilities while sleepy [2]. Thus developing an effective system for detecting drowsiness is an important issue for real-life driving. A large number of researches have been conducted to investigate driver drowsiness using different methods, such as such as eye blinking, heart rate, pulse rate or skin electric potential, particularly, brain waves, as a means of detecting human cognitive state [3-5]. The EEG signal is a representation of the brain's electrical activity recorded from electrodes placed on the scalp which can includes abundant information of the cognitive states such as alertness and arousal. Numerous studies suggest that delta (1-3 Hz), theta (4-7 Hz), and alpha (8-12Hz) activities are highly correlated with fatigue, drowsiness, and poor task performance [6-8]. It has been used to assess the driver's performance for many years. For instance, the authors of [9] found that three indices: beta/alpha, beta/(alpha plus theta), and theta/alpha were able to distinguish the feedback conditions. The authors of [10] suggested a system that combines EEG power spectra estimation, independent component analysis (ICA) and fuzzy neural network models to estimate drivers' cognitive state in a dynamic virtual reality based environment. The authors of [11] use the neural network model, applied to EEG power spectrum, in an

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auditory monitoring task and showed that a continuous, accurate, noninvasive, and near real-time estimation of an operator's global level of alertness is feasible. Other authors of [12] proposed a method to detect departure from alertness. They showed that the EEG power in the alpha and theta bands is highly correlated with changes in the subject's cognitive state with respect to drowsiness through driving performance.

The aim of the present study is to develop an effective EEG-based driver drowsiness monitoring system by analyzing the changes of brain activities in a simulator driving environment. Firstly, Independent component analysis (ICA) is performed on EEG data to remove artifacts. Then, eight EEG-band powers-related features: beta, alpha, theta, delta, (alpha plus theta)/beta, alpha / beta, (alpha plus theta)/(alpha plus beta) and theta / beta are extracted from the preprocessed EEG signals by employing the Fast Fourier Transform (FFT). Subsequently, fisher score technique selects the most descriptive features for further classification. Finally, Support Vector Machine (SVM) is employed as a classifier to distinguish drowsiness level. Figure1 shows the framework of our SDPEA system.

This paper is organized as follows. Section 2 introduces the experiment setup and data acquisition. In Section 3, we introduce the data preprocessing and feature extraction. The results and data analysis are presented in Section 4. Finally, Section 5 draws the conclusion.

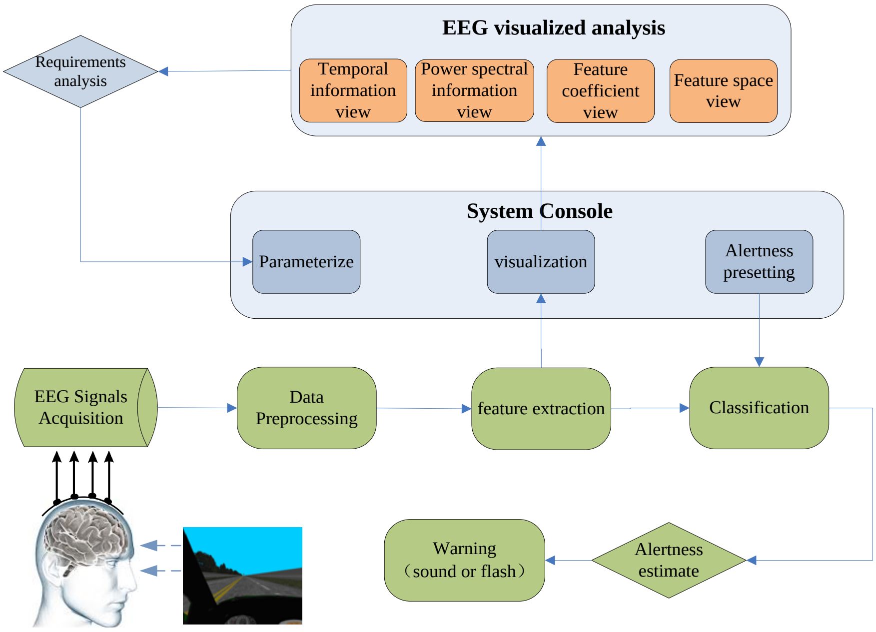


Figure 1. SDPEA System Block Diagram

2. Experiment Setup and Data Acquisition

2.1. Subjects

Nine healthy subjects (male students, aged between 21 and 30) participated in a sustained-attention driving task. Statistical reports [13] showed that the drowsiest time occurs from late night to early morning, and during the early afternoon hours. During these periods, drowsiness often occurs within one hour of continuous driving. To easily induce drowsiness, the experiment began in the early afternoon (13:00–14:00) after lunch and lasted for about 90 minute. The subjects are required to lie on a bed when they feel sleepy, close their eyes, and try to relax. During this time, a short period of soft music is presented to the subject about every 10 minutes.

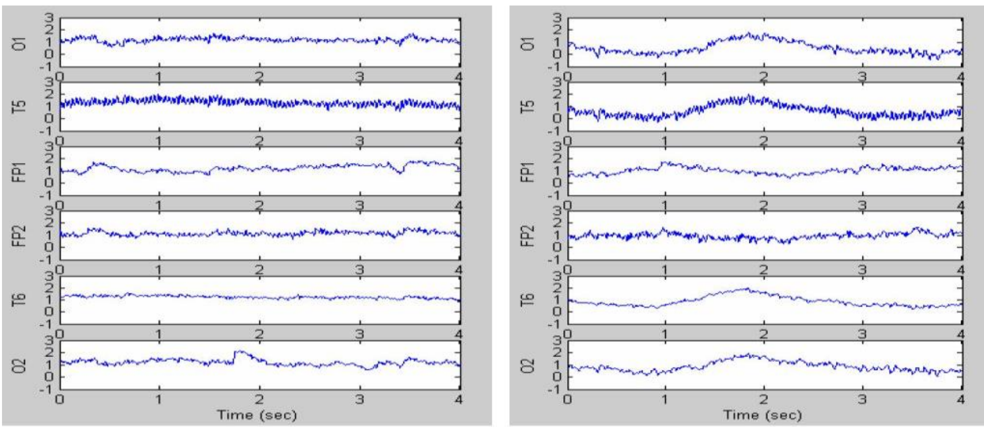
The music lasts 10 seconds with the volume that does not disturb the sleeping subjects. The subjects are required to open their eyes to demonstrate they are awake if they hear the music. The whole process is recorded by a digital video camera. Figure 2 shows the experiment setup and data acquisition procedure.

Figure 2. Procedure of Experiment Setup and Data Acquisition

2.2. Data Acquisition

64channels of EEG signals including 62 channels of EEG and 2 channels of EOG were recorded in a shielded room by a 64 channel high-resolution EEG/ERP Systems (SynAmps2, Neuroscan) sampled at 1000 Hz, and are filtered between 0.1 and 100 Hz. The electrodes are located at the positions of the 10-20 international electrode-positioning standard: FP1,FPZ, FP2, T3, T4, F7, F5, F3, F1, FZ, F2, F4, F6, F8, FT7,FC5, FC3, FC1, FCZ, FC2, FC4, FC6, FT8, T5, C5, C3,C1,CZ,C2, C4, C6, T6, TF7, CP5, CP3, CP1, CPZ, CP2, CP4, CP6,TF8, P7, P5, P3, P1, PZ, P2, P4, P6, P8, PO7, PO5, PO3, POZ,PO4, PO6, PO8, CB1, O1, OZ, O2 and CB2. Reference points are put on the papillary place behind two ears.

After each experiment, we use the feedback information from the subject and combine with the video recording to manually label the wakefulness state and sleepiness state of each subject. The EEG data were labeled, only when both sides had the same vigilance state assessment. Figure 3 shows six channels' EEG signals of subject 5 in wakefulness state and sleepiness state.



(a) Wakefulness State (b) Sleepiness State

Figure 3. EEG Signals of Subject 5 in Wakefulness State and Sleepiness State

3. Methodology

3.1. Data Preprocessing

Excluding contamination of EEG activity (*e.g.*, eye movements, blinks, cardiac signals, and muscle activity and line noise) is a serious problem for EEG classification and analysis. One way of dealing with this problem is to simply reject segments of EEG with unacceptable amounts of noise. However, this may result in an unacceptable amount of data loss. ICA is a good method for blind source separation, which has shown to outperform the principal component analysis (PCA) in many applications. In particular, it has been applied in the extraction of ocular artifacts from the EEG, where PCA could not separate eye artifacts from brain signals, especially when they have comparable amplitudes.

The ICA model can be stated as follows.

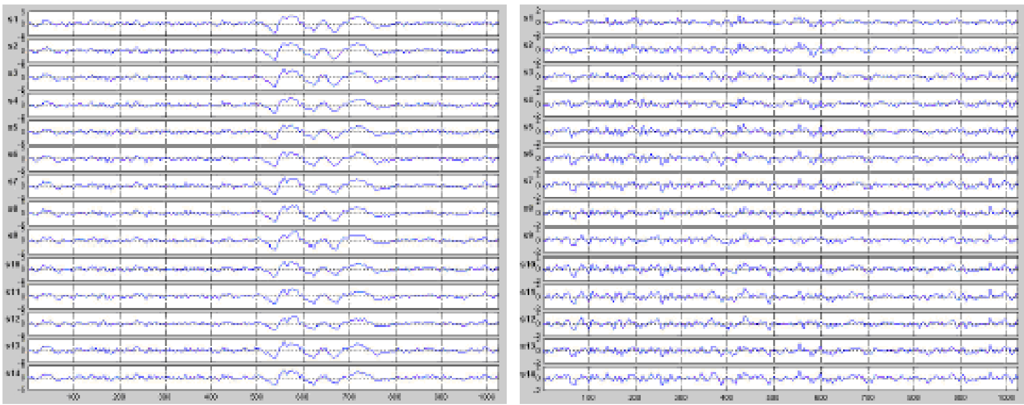
$$X(i) = AS(i) \tag{1}$$

Where $X(i)$ represents the observed n-dimensional data vector. $A = [a_{nm}]$ represents the mixing matrix and $S(i) = [S_1(i) \ldots S_m(i)]$ represents the independent source signals. Both A and $S(i)$ are unknown. Other conditions for the existence of a solution are (a) n=m (there are at least as many mixtures as the number of independent sources), and (b) up to one source may be Gaussian. Under these assumptions, the ICA seeks a solution of the form:

$$Y(i) = BX(i) \tag{2}$$

Where B is called the separating matrix, and $Y(i)$ is the estimation of $S(i)$.

In this work, we will apply cICA (see [14]) for the artifact rejection in EEG signal analysis. Figure 4 shows the artifact removal of EEG using cICA.



(a) Raw EEG signal (b) Corrected EEG signal

Figure 4. The cICA for Automatic Artifact Removal of EEG

3.2. Fisher Score

After obtaining feature vectors by employing the Fast Fourier Transform (FFT), Fisher score is utilized to further remove redundant features, and select most significant discriminative patterns. Fisher score is a discriminative measure of an individual feature for binary classification tasks.

It is defined as,

$$Fisher\ score = \frac{\left\| \mu_1 - \mu_2 \right\|^2}{\sigma^2{}_1 + \sigma^2{}_2} \tag{3}$$

where μ_1 and μ_2 denote the means of class 1 and class 2 over an individual feature, and σ_1 and σ_2 denote corresponding variances.

For each individual feature, its fisher score is computed, and then features with the n-largest Fisher scores are retained as the most significant features, and other features are discarded as the discriminatively redundant features. In this step, the most significant discriminative patterns are obtained from the corresponding projection matrices of the retained features. Figure 5 shows the mean changes in Scalp topographies of the delta, theta, alpha, beta, (alpha plus theta)/beta, alpha / beta, (alpha plus theta)/(alpha plus beta) and theta / beta power at wakefulness state, sleepiness state, and differentials.

3.3. SVM for Classification

Support Vector Machine was used as the classifier model in this work because of its good classification performance and its speed of training [15]. SVM can be described as,

$$\frac{1}{2}\left\| w \right\|^2 + C\sum_{i=1}^{N}\xi_{i^2} \qquad \text{Subject to } y_i(w^T x_i + b) \geq 1 - \xi_{i^2}, (i = 1,...,N) \tag{4}$$

where $C > 0$ is a regularization parameter and ξ_i is the slack variable. w is the weight vector and $b \in R$ is the offset. x_i is the support vector of the training data and $y_i \in \{-1, 1\}$ is their corresponding class label.

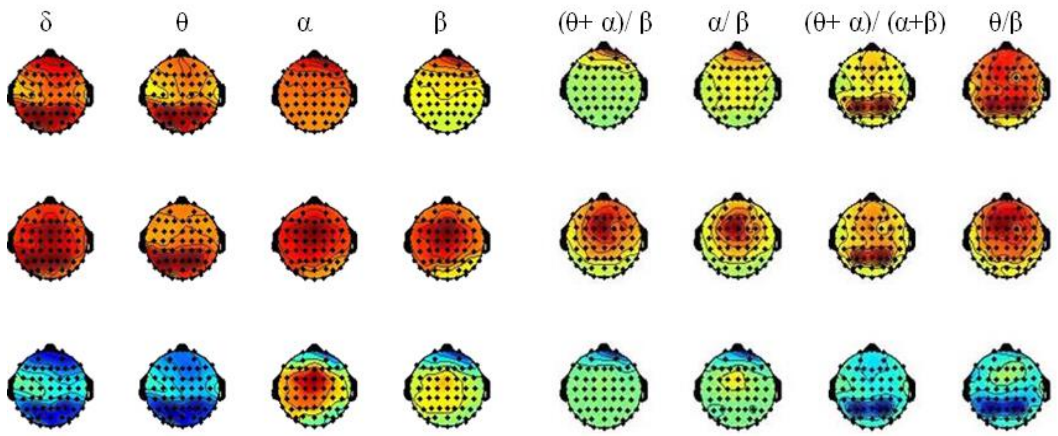


Figure 5. Scalp Topographies of Eight Features Extracted from Subject Six

The Support Vector Machine is based on the idea of separating the training data x_i with labels y_i by means of a linear hyperplane, such that the minimal distance of each point from the hyperplane, *i.e.*, the so-called "margin", is maximized. The regularization parameter C controls the tradeoff between two objectives: a smaller C will result in a larger margin around the hyperplane, but may cause a higher error on the training data. A larger C will decrease the training error, but possibly reduce the generalization error by enlarging the margin. In this study, we used a SVM with a radial basis function (RBF) kernel with γ = 0.1. The SVM was trained with regularization parameter C = 0.8, which places an upper bound on the fraction of error examples and lower bound on the fraction of support vectors [16].

4. Results and Data Analysis

The proposed SDPEA system was designed using Matlab, and the graphical user interface (GUI) of SDPEA system is shown in the Figure 6. From the GUI, the raw EEG signal recording, the band powers, the ratios of band power, the band powers and ratios can be observed clearly. Furthermore, the alert level, real time state of alert grades and record of alerts are also displayed in the GUI.

Table 1 summarized the results of nine subjects' classification rates in eight different features using SVM method. The first row denotes the different subjects. The first column denotes the different band power features. From the table, it can be seen that the accuracy of classification in the band power features of alpha, beta, (alpha plus theta)/beta, and alpha / beta are better than others.

We categorize alertness levels into four states, namely wakefulness (W), middle state 1 (M1), middle state 2 (M2), and sleepiness (S). Figure 7 shows the performance of subject 3 during an 80-minute's length driving simulation experiment. X-axis is the time in minute. This result correctly partitions the labeled wakefulness EEG and the sleepiness EEG. From this figure, we can see that there are some overlaps. These overlaps do not mean that two states appeared at the same time but because of limited resolution of the figure. During the spectrum analysis, we find that although the EEG spectrum changes gradually, there still exit 4 distinguishable periods, and which match the periods of clustering states harmoniously. Therefore, we can use the EEG band powers for the alertness assessment. However, there is also a certain inefficiency using band powers. The band powers are prone to be contaminated by the artifacts, including both ocular and muscle artifacts. So, careful data preprocessing is important for drawing any validated conclusion from the band power results.

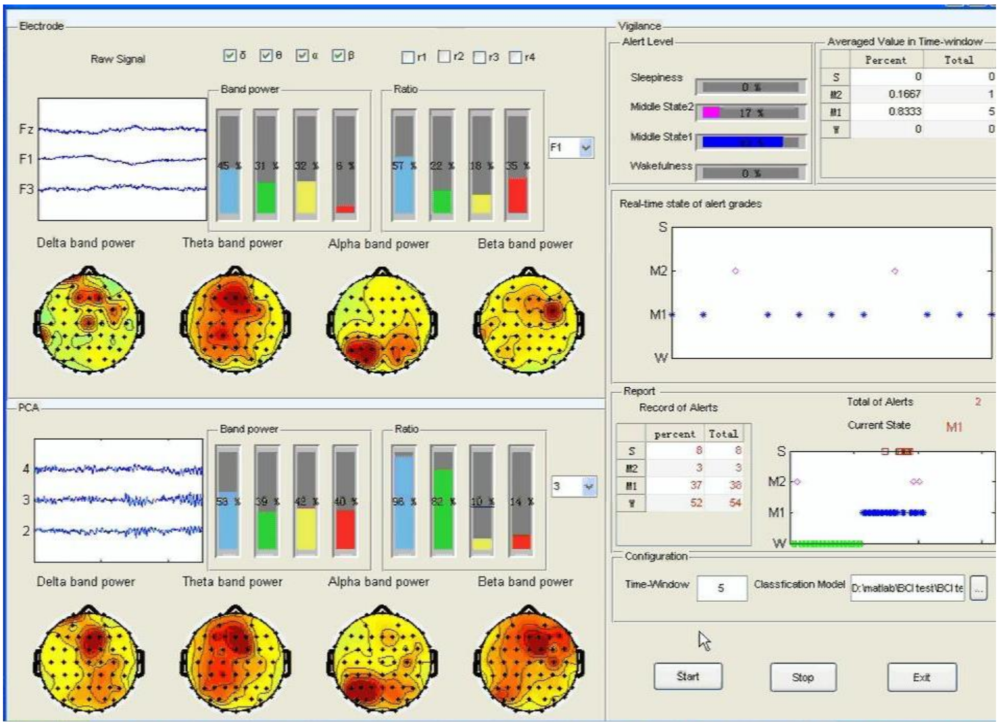


Figure 6. GUI of SDPEA System

Table 1. The Classification Rates using Different Features

subjects	S1(%)	S2(%)	S3(%)	S4(%)	S5(%)	S6(%)	S7(%)	S8(%)	S9(%)
δ	74.5	85.5	89.9	64.7	95.8	86.2	94.4	75.0	83.3
θ	60.5	96.4	87.0	80.4	83.3	89.7	100	80.0	100
α	72.7	100	89.7	84.3	97.9	93.1	100	85.0	100
β	74.5	100	97.1	90.2	100	93.1	100	70.0	100
(θ+α)/β	89.1	92.7	79.7	80.4	97.9	96.5	94.4	75.0	100
α/β	72.8	85.5	95.7	68.6	93.8	100	100	85.0	100
(θ+α)/(α+β)	66.1	61.8	87.0	90.2	97.9	79.3	55.6	65.0	77.8
θ/β	70.6	72.7	82.6	92.2	93.8	79.3	88.9	85.0	83.3

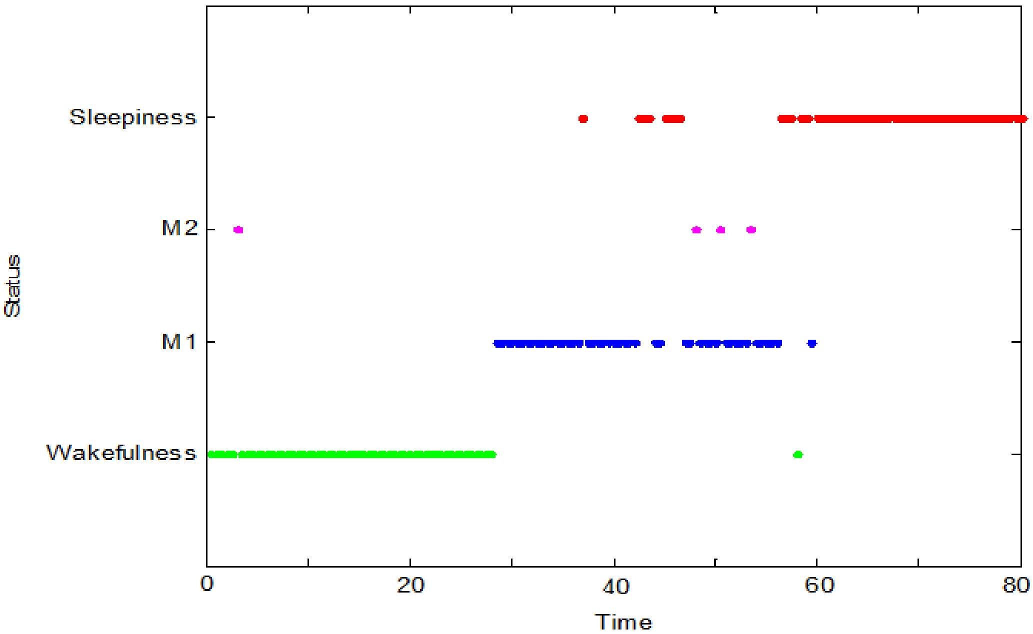


Figure 7. The Clustering Result

5. Conclusions

In this paper, we have developed a novel effective EEG-based driver drowsiness monitoring system by analyzing the changes of brain activities in a simulator driving environment, which using ICA method to remove artifacts, then using an FFT analysis to estimate the power spectrum density and band powers features were extracted, SVM method were employed as classifier to distinguish alertness level finally.

Although we used the SVM methods to classify workload, there were still some issues that had to be addressed. Using the traditional machine learning methods for alertness state classification is problematic. The selection of features is prone to involve non-workload components. Many studies used a large feature vector for classification, for instance, delta, theta, alpha, beta, and gamma from different electrode sites. Furthermore, the classifier training with the predefined labels responding to the predefined task load might also be problematic. The label assigned for the classifier training may itself be incorrect, which also leads to an incorrect classifier. Therefore, the quantification of workload using band powers requires improved mathematic algorithms.

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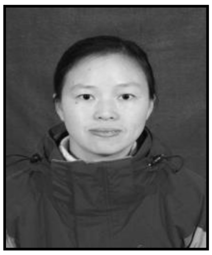

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