ESTIMATE VIGILANCE IN DRIVING SIMULATION BASED ON DETECTION OF LIGHT DROWSINESS

Hong-Jun Liu, Qing-Sheng Ren and Hong-Tao Lu
MOE-Microsoft Laboratory for Intelligent Computing and Intelligent Systems
Department of Computer Science and Engineering, Shanghai Jiao Tong University, Shanghai 200240, China

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Abstract: Avoiding fatal accidents caused by low vigilance level in driving is very important in our daily lives. Electroencephalography (EEG) has been proved very effective for measuring the level of vigilance. In this paper, we identify light drowsiness state from other states to estimate vigilance level decline by using support vector machine (SVM). Light drowsiness EEG is marked by alpha increasing to 50%. Alert EEG is marked by dominant beta activity and other EEG is labeled as sleep state. Samples of EEG data are trained in SVM program by using 4 features from each frequency band. Mutual information based feature selection method is used to reduce the dimension of features. The accuracy in classification of alert and light drowsiness reaches 91.5% on average.

1 INTRODUCTION

Studies on vigilance have shown that vigilance analysis is very useful to our daily lives (Weinger, 1999). Low vigilance level while driving is a serious problem and is believed to be a direct cause of related accidents (Lal and Craig, 2001). Light drowsiness, which is dangerous for drivers, is a state before entering sleep. If symptoms of vigilance level decline and light drowsiness appearance can be detected and used to warn the driver, effective measure will be taken and accidents will be prevented.

As there is no generally accepted international standard on classification of different vigilance levels, some studies used their own methods to divide vigilance into several categories (Makeig et al., 1996; Lin et al., 2006; Shi et al., 2007), and there are also some studies followed sleep classification criterion (Niedermeyer and Silva, 2004; Schomer, 2007) which can precisely divide driver vigilance level into alert and sleep state (Yeo et al., 2009; Li et al., 2008). However, it will be too late if driver already falls into sleep. For this reason, the vigilance level of drivers before sleep needs further classification to predict the onset of sleep.

In our study, we use EEG for vigilance analysis. We divide the vigilance into 3 states from high level to low level following Hori's sleep classification (Hori et al., 1994). Light Drowsiness state is between state 1 which is alert and state 3 which is sleep. EEG in light drowsiness state is characterized as 1) alpha activity increase to 50% of EEG data; 2) eye closures greater than 0.5s. The performances of the driver at light drowsiness are mostly characterized by decline of eye blinking frequency, long time closure of eyes and great decline of driving operation. EEG in alert state is characterized as 1) EEG activity in the beta frequency; 2) inter-eye blink intervals of 6-8s (Doughty, 2002) and other EEG is labeled as sleep state. As the eye blink patterns characteristic in each state also shows in low frequency band in EEG data, the Electro-Oculogram (EOG) artifact is not removed in our analysis process. Considering the above vigilance state transition properties, we extract features in each frequency band. Experimental results show that light drowsiness state can be correctly distinguished from alert state and the sleep state by EEG.

This paper is organized as follows. In Section 2, vigilance experimental setup is introduced and the method of estimating the vigilance level is presented. In Section 3, experimental results are described. Finally, conclusions are given in Section 4.

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2 METHOD DESCRIPTION

2.1 Experimental Setup and Data Collection

In this study, ten healthy young volunteers, aged from 18 to 28 years old, were selected to take part in the driving simulation experiment. They were required to abstain from alcohol and caffeine drinks one day before the experiment.

In the driving simulation environment, each subject was required to drive with a steering wheel. There is a 19' LCD screen which displays the simulating driving scenes in front of the subject. The simulated driving map consists of two long straight roads and two spin turns. The completion of a circle needs about 10 minutes at the speed of 60km/h. The sceneries are so monotonous that the subject may feel drowsy easily and even fall asleep. The simulated driving lasted one and half an hour which was carried on in special room whose temperature was about 27°C and humidity was between 40% and 60%.

The experiment data was acquired through 64 channels of signal system including 62 channels of EEG and 2 channels of EOG. Electrodes are arranged based on extended 10/20 system. The Ag/AgCl electrodes are mounted inside the cap subject wore with bipolar references behind ears. The EEG signal was recorded at the sampling rate of 100Hz while the subject's facial expression was recorded by a DV camera in the same time, which was used for labeling the EEG data. The EEG data from five subjects, who had shown a tendency to fall asleep during the driving simulation, were selected for data analysis in this paper.

2.2 Data Processing

The whole process consists of 3 steps. In the first step, EEG pulse artifacts were removed by visual inspection, and then the raw EEG data were filtered using Finite Impulse Response (FIR) filter with a pass band of 1-40Hz. The filtered data were manually classified into 'alert' and 'light drowsiness and sleep' classes based on inspection of the video using two key identifiers:1) dominant EEG activity and 2) eye blink patterns. The EEG data were labeled on two kinds of time window with 5s and 15s. These data were randomly divided into 50% of the test set and 50% of the training set. In the second step, features were extracted from the filtered 62 EEG signal channels, and then a mutual information based feature selection method was used to reduce the dimension of feature. In the last step, SVM was used in classifying the EEG feature data into two classes.

2.3 Feature Extraction

In this study, features are extracted by transforming each afore-mentioned 5s or 15s EEG epochs into feature vectors. Various features are extracted based on the power spectrum of EEG epochs, capturing both spatial and temporal information that are useful for optimally distinguishing from 'alert' to 'sleep' EEG epochs. We use Fourier transform to extract the Power Spectral Density (PSD) on each EEG data epoch. The PSD was then divided into 5 segments according to the 5 standard EEG frequency bands: delta (1-4Hz), theta (4-8Hz), alpha (8-13Hz), beta (13-20Hz) and gamma (20-40Hz) according to (Noachtar et al., 2004). The following four features were extracted for each frequency band:

2.3.1 Power Proportion (PR)

Because energy in each frequency band of every person is quite different from each other, especially in alpha rhythm, total power of each band is useless. The proportion of the energy in each band to total energy of channel is very important to identify the vigilance level. For example, the state in which alpha dropout and theta appearance can be classified into sleep state 1 according to (Niedermeyer and Silva, 2004).

2.3.2 Variance of Power (VP)

Variance of power can characterize energy dispersion in each frequency band. If subject falls into light drowsiness state, energy in his alpha band will center on a particular value range and VP will reduce in the same time.

2.3.3 Average of Frequency (AF)

It is defined as

$$AF = \sum_i P(f_i) \times f_i \tag{1}$$

where f is frequency and P(f) is the probability distribution of frequency. It can reflect the changes in frequency over time.

2.3.4 Variance of Frequency (VF)

Variance of frequency is different from the feature VP whose value is much larger. If the spectrum for a considered frequency band has two frequency peaks, the value of VF will become larger. AF and VF have been proved very useful in multilevel vigilance EEG classification (Shen et al., 2007).

2.4 Feature Selection

After feature extraction, each EEG epoch is converted into a 1240×1 vector of quantitative EEG features ($62\ channels \times 5\ frequency\ bands \times 4\ kinds\ of\ features$). The number of features is so large that the computing speed and correct rate of classification in light drowsiness detection will both decline. Information of adjacent channels also has redundancy. For these two reasons, we use a mutual information based feature selection method called mRMR (Peng et al., 2005) to reduce the dimension of feature vector. This method selects feature subset by optimizing max-relevance between feature subset and target class, and min-redundancy among the feature subset.

Denote the i-th feature of EEG signals by x_i and the vigilance states by c. We just use labeled information mentioned above to select the feature subset. Let $I(x_i;c)$ denote the mutual information between x_i and c. Then the relevance between feature subset S_m and class c can be defined as

$$D = \frac{1}{|S_m|} \sum_{x_i \in S_m} I(x_i;c) \tag{2}$$

and the redundancy among the feature subset can be defined as

$$R = \frac{1}{|S_m|^2} \sum_{x_i, x_j \in S_m} I(x_i;x_j) \tag{3}$$

where $I(x_i;x_j)$ is the mutual information between x_i and x_j. The criterion of mutual information based feature selection method is to maximize $D-R$. The criterion operator can be defined as

$$\Phi = D - R. \tag{4}$$

Thus, the select feature subset should maximize Φ. In practice, we reduce the number of features to about 10%.

2.5 Light Drowsiness Detection

SVM is a supervised learning method widely used for classification and regression (Boser et al., 1992; Cortes and Vapnik, 1995). In the research of vigilance field based on EEG, SVM has been proved a pretty effective classifier (Yeo et al., 2009). Classification accuracy rate usually can be 90% or more. In this study, SVM is also used for the purpose of classification between 'alert' and 'light drowsiness and sleep state' after the feature selection process. For the reliable detection of drowsiness, a nonlinear SVM is used with the popular Gaussian kernel.

3 EXPERIMENTAL RESULTS

3.1 Choose Optimal Feature Number

After feature selection which is described in section 2.4, 1240 features are ordered by descending according to their values of Φ. Figure 1 shows the curve in which classification error rate changes with the number of features for different subjects. Depending on the error rate curve, we choose 150 features as the number of features in final classification.

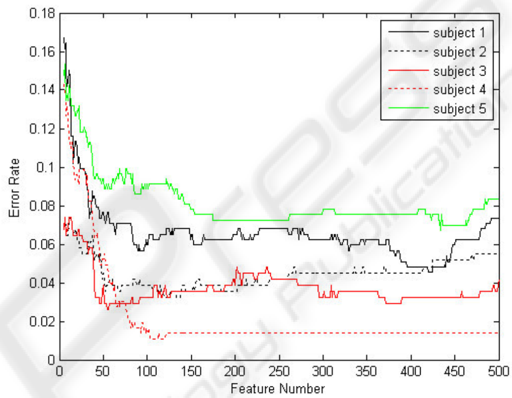

Figure 1: SVM error rate using mRMR features.

3.2 Classification Rate

For the five chosen subjects, we test both SVM classification correct rate between 'alert' and 'light drowsiness and sleep state' with 5s and 15s time window. The training and test accuracies for these subjects are shown in Table 1. The result on test date reaches 91.5% on average.

Table 1: The training and test correct rates of 5 subjects.

	Sub1	Sub2	Sub3	Sub4	Sub5
5s Training	98.75%	99.86%	99.24%	100%	99.52%
5s Test	87.50%	92.60%	91.13%	97.71%	88.72%
15s Training	100%	100%	100%	100%	100%
15s Test	92.35%	93.48%	91.60%	97.75%	91.13%

The result of classification can be shown in Figure 2. Overlapping part in the figure describes that the subject fought for keeping alert.

According to the features of sleep state 1 and sleep state 2 in EEG (Schomer, 2007), we also labeled sleep states for each EEG data with 5s time window. The result in which sleep state is extracted can be shown in Figure 3. The correct rate of separating 'sleep state' from 'light drowsiness and sleep state' can reach to 98%.

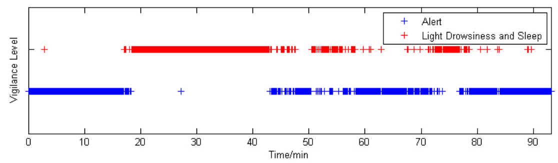

Figure 2: Classification of two vigilance states.

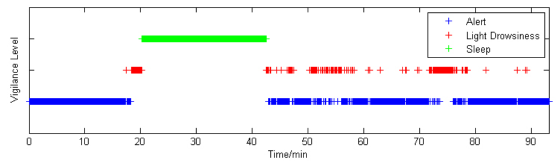

Figure 3: Classification of three vigilance states including sleep state.

4 CONCLUSIONS

In this paper, an EEG signal processing method is presented for distinguishing 'light drowsiness' from other vigilance level in driving simulation environment. Firstly, we extract 4 features for each frequency band in every EEG channel. Then we use a mutual information based feature selection to reduce the dimension of features. Finally, SVM is used to classify light drowsiness state from alert on labeled EEG data. Our experiment results give over 91% average accuracy with 5s time resolution for five subjects. This study also shows that the light drowsiness state can be classified very precisely from alert state. According to the result of this classification, accidents caused by driver sleep can be prevented efficiently.

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