Vigilance Estimation Based on Statistic Learning with One ICA Component of EEG Signal

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Abstract. EEG signal has been regarded as an reliable signal for vigilance estimation for humans who engage in monotonous and attention demanding jobs or tasks, research work in this area have made satisfying progress and most of these methods or algorithms are based on the pattern recognition and clustering principal. Inspired by the HMM(Hiden Markov Model), we proposed a probability method based on the (PSD) Power Spectral Density distribution of the energy changes to estimate the vigilance level of humans using only one ICA(Independent Component Analysis) component of EEG signal. We firstly extract the specific frequency band energy feature using (CWT)Continuous Wavelet Transform, then analyze different vigilance states energy data to get the energy distribution information and vigilance states transformation probability matrix, finally use the energy distribution and vigilance states transformation matrixes to estimate vigilance level. Experiments result show that the proposed method promising and efficiently.

Keywords: Band Frequency, Energy, Histogram, Probability.

1 Introduction

It's a very difficult task for humans keeping their vigilance level at a certain level who take on monotonous and attention demanding jobs or tasks such as driving,guarding, etc., so research on vigilance level estimation is a very important work for reducing the traffic accidents and avoiding the potential accident disaster. Many research work have been done in this area which based on biomedical feature such as head position estimation, eyelid movement, face orientation and gaze movement (pupil movement)[1], etc. and get many satisfying experiment result. EEG signal have been regarded as an efficient methods used for vigilance estimation and many efforts have been made in this field and got some significant progress, however, due to the nature of low signal-to-noise ratio for EEG signals, vigilance estimation based on EEG into application still face many obstacle to remove. Many algorithms and approaches have been proposed or used in the EEG signal analysis, CSP(common spectral pattern), ICA and PCA(Principal Component Analysis)have been used in dimension reduction or feature selection. FFT(Fast Fourier Transform), DWT(Discrete Fourier Transform) and STFT(Short Time Fourier Transform) are also applied into the

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feature extraction and some other pre-processing work and many classifier such as SVM(Support Vector Machine), HMM and SR(Sparse Representation) are the mostly used for estimating the vigilance level[5]. some supervise cluster and unsupervise cluster method have also been applied into the research work. However, Most of previous research are based on pattern recognition and clustering principal, human vigilance is divided into 3 or more degrees such as wake, drowsy and sleepy), so the humans' vigilance estimation work is to classify the EEG signal into different classes which corresponding to different vigilance degrees. There exist two drawbacks in this algorithm framework, first, as we all know that vigilance changes is a continuous process, mechanically segmenting the process from wake to sleep into different classes can not accurately reflect the true characteristics of these changes. second, it is not an easy job to label the vigilance level exactly. Many researchers combine the EEG and EOG or other signal to label the vigilance states and then a variety of biological characteristics are used to predict the degree of alertness and get a relatively high estimation accuracy, however, which will result in much computation cost. In this paper, we consider to use both the error rate and response time of the participant's test in simulation environments to determine different vigilance states. As mentioned above, EEG recoding is a non-stationary and extremely sensitive signal and can easily be polluted by the noisy, so noisy remove preprocessing work is important for the following vigilance estimation stage.In this paper we adopted the method proposed by [2] to remove the artifacts based on the pattern recognition theory. EEG data used in this paper are collected in a simulation environment from one hundred people aged 18-28 and we only use one ICA component and a complex wavelet transformation was used to extract the γ-band frequency, 1-3 order transformation probability matrix and different states generator probability matrix based on energy value are also got from the above band frequency. Then we apply the state transformation matrix and states generator probability to estimate vigilance degree.

This paper is structured as follows: In section 2 the experiment environment for EEG data acquisition is introduced. In section 3, the EEG preprocessing methods are given, and in section 4 the experiment result is presented. Finally, conclusions and future work are given in section 5.

2 Data Acquisition

More than one hundred young men aged 18-28 participated in our EEG vigilance analysis data collection experiment. This experiment is a monotonous visual task, Subjects were required to sit in a comfortable chair, two feet away from the LCD and wear a special hat with 64 electrodes connected to the amplifier of the NeuoScan system. In front of the subjects is a LCD which four colors of traffic signs were presented randomly and each color has more than 40 different traffic signs. The interval and duration of the traffic signs displayed on the screen is 5.5$\sim$7.5 including 5$\sim$7 seconds black screen and 500 millisecond respectively. The subjects are asked to recognize the signs' color on the screen and press the corresponding color button laid on the response pad. We do these experiments in a small soundproof room with normal illumination. Each experiment started at 13:00 after lunch and lasted for one hour or more. Every subject participated two experiments, One data was for training and the other is for testing.

For each session, the visual stimulus sequence and response sequence are recorded by the NeuroScan Scan software sampled at 500Hz. Meanwhile, a total of 62 EEG channels are recorded by the NeuroScan system sampled at 500Hz synchronously, and filtered between 0.1 and 40Hz using band-pass filter. The electrodes are arranged based on extended 10/20 system with a reference on the top of the scalp.[3]

3 Method

In this section, we will describe the method we used to estimate humans' vigilance degree based on EEG recording. To begin with, we will give the introduction of the pre-process work. Then we will present our vigilance degree estimation algorithm based on the γ-band frequency energy distribution.

3.1 Data Preprocessing

In the data pre-processing stage, we first remove the EEG signals collected using the damaged channels and then eliminate the artifacts caused by the EMG and EOG signal by the method in [2]. As we all know that the potential generated on the scalp where the electrode placed on is the summation of the potential value generated around it even all of the scalp, so the ICA (Independent Component Analysis) method is applied to the EEG signals to get the mapping matrix which used to find the approximate independent components.

3.2 Feature Extraction

In this stage, we will implement the feature extraction operation. Due to the non-stationary nature of the EEG signal from each electrode of the NeuroScan system, the sampling data of EEG are divided into many overlapping epochs and each epoch contains 200 new sampling data and 200 duplicate data from the previous epoch, so each epoch corresponds to EEG signal of 4 seconds and for each epochs, we use the ICA mapping matrix to get the independent component. We choose only one component from the ICA components and then to extract the energy feature using the Continuous Wavelet Transformation. The wavelet function we used in our experiment is the complex Morlet wavelet function because of its good resolution both in time domain and frequency domain. The function defined [4] by

$$\psi(x) = \frac{1}{\sqrt{\pi f_b}} exp\{2i\pi f_c x\} exp\{-\frac{x^2}{f_b}\} \tag{1}$$

where f_c denote denote the central frequency, and f_b is a bandwidth parameter, f_c and the variance σ_f are related by $f_b = \frac{1}{2\pi^2\sigma_f^2}$. In this way we can accurately obtain the wavelet coefficient of the EEG signals at the specific time and frequency-band by adjusting the parameter values of the Morlet wavelet function. In this paper, we tend to set $f_c = 35$ and $f_b = 5$, which corresponding to the γ-band frequency, because the γ-band energy can give a better estimation result. After continues wavelet transformation operation, we get the energy value of the γ-band frequency of all of vigilance states data including wake, drowsy, sleep states and the transition between states.[5] We don't want to give an exact division about human's vigilance, what we need is just the task of non-wake states detection.

3.3 States Determination

Generally speaking, precision state division is an almost impossible job, it is the same for us. Here we consider both the response time of the recognition behavior and recognition error ration of the subjects' in the task of color recognition as the indicator for vigilance state determination. The following is the response time and the recognition error rates of one subject. From the left two charts we can see that the first experiment data is divided into 1171 overlapping epochs and from the 1st to the 561th epochs, in this session the subject is in the drowsy states, during which the subject cannot response to the color stimuli timely and exactly. Drowsy state in this experiment data can easily be determined, however, not all of experiment data in such case. There are a total of 1935 epochs in the second experiment data and the top is response time graphic and the below is the color judgement error rate graphic. In the response time graphics, the shortest response time is about 300 milliseconds(at the 394th epochs) and the longest is 1000 milliseconds(at the 968th epochs). In the session between 1st

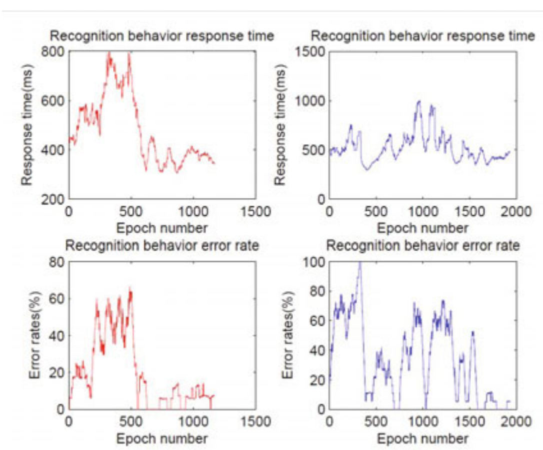

Fig. 1. Response time and recognition error rate. Figure 1 is the four charts about response time and error rate of one subject in two experiments. The left two charts are the response time and error rate charts respectively of one subject in the first experiment and the right two are the second experiment result.

and the 394th epochs the subject's response time is not very long, but in the error rate graphic the judge error rate is above 70%. We regarded this session to be the drowsy states in which states the subject can able to timely respond to external color stimuli but can hardly make the right judgments. From the 395th epochs to the 1586th, the error rates is very hight and only a few session has a relatively low error rate, in this period of time, we can believe that the subjects in a state of extreme fatigue, the session between the 1587 $\sim$ 1935 epochs, the subject in the state of clear-headed. As mentioned previously, We compute the wavelet coefficient of the γ-band frequency find that human's vigilance states have a close relationship with the energy's distribution. We find that the energy value is inversely-proportional relation to the vigilance degree, generally speaking, energy is low when the humans in the state of clearly-headed and vice versa at the γ-band frequency. In order to give more detail evidence, We also give

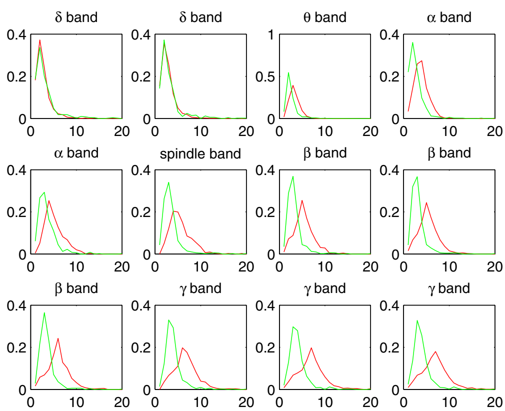

Fig. 2. Energy distribution of wake data and drowsy data. In each graphic, the red line denote the wake state energy distribution, while the green line is the drowsy state energy distribution.From Figure 2, we know that it is nearly impossible to distinguish between the wake and drowsy states using the δ-band frequency, the β or γ-band frequency may be the optimal choice in the vigilance estimation work based on energy distribution.

the energy distribution of EEG recordings in wake and drowsy states, actually, because of the difficulties in states determination work, we can only give approximate estimation about the energy distribution. In Figure 2, we illustrator the energy distribution of wake and drowsy states at different band frequency using histogram with 20 bins.

3.4 Probability Matrix Computation

Inspired by HMM, we try to estimate human's vigilance degree using the probability method. Our algorithm do it by the following step:

1. we calculate the energy distribution's histogram in different vigilance states as well as the whole process histogram get three vectors V_c, V_d, V_w where V_c corresponding to the clearly-headed state, V_d to drowsy state and V_w to the whole process. $V_i(i = c, d, w)$ are matrixes where each element denote the number of the energy in the corresponding to range.
2. Compute the probability in the time sequence by:

$$P_c = V_c/V_w, \quad P_d = V_d/V_w \tag{2}$$

   Actually, P_c and P_d are the posterior probability which means that the probability of the subject in the clear-headed states or drowsy state given the specific band frequency.
3. We can also get 1-order, 2-order, 3-order states transformation matrix T_1, T_2, T_3 by the event probability P_c and P_d. Basically, we can just only compute posterior probability one matrix P_d or P_c to detect the drowsy degree or vigilance level, when the human's drowsy degree is high or vigilance level is low the controlling center will send out a warning.
4. Compute the states probability given the vector V by the following:

$$p_d = P_d(V), \text{or} \quad p_c = P_c(V) \tag{3}$$

   We can also combine the previous state into the computation of the states probability by:

$$p_d = P_d(V) + \sum_{i=-N}^{-1} T_i(V)W_i \tag{4}$$

   where T_i denote the transformation probability matrix, W_i is the weight and N is the order.

4 Experiment Result

In order to test our algorithm, we used two data set collected from the same subject in two experiment, firstly, we compute the wake and drowsy state PSD of the training data by using histogram method and get the state occurrence probability matrix and 1-order, 2-order and 3-order states transformation matrixes; then we used the fatigue state occurrence probability matrixes and 1-order, 2-order and 3-order states transformation matrixes to estimate the wake state degree from the first data set, the experiment result is give by Figure 3. From the Figure 3, we can see that, basically, our algorithm can make a relative accurate estimation to the human's vigilance changes,and just like what we thought, the β, λ-band frequency give better predictions result than the other band frequencies energy because of the the β, λ band frequency have more exact determination bounder which the illustrator displayed in Figure 2.

Then we use the wake state occurrence probability matrixes and 1-order, 2-order and 3-order states transformation matrixes to estimate the wake state degree from the first data set and also give a satisfy estimation result which

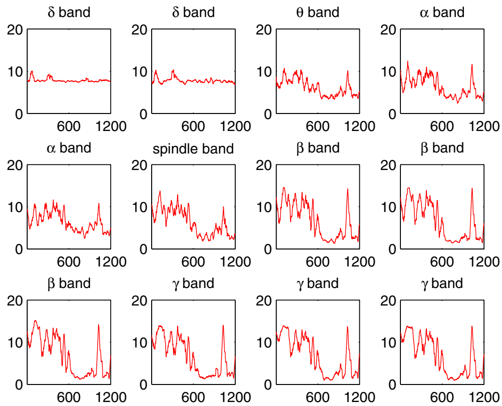

Fig. 3. Drowsy State Estimation Result over Train Data. The horizontal coordinate denote the number of epoch and vertical coordinate is the probability score of drowsy state occurrence.

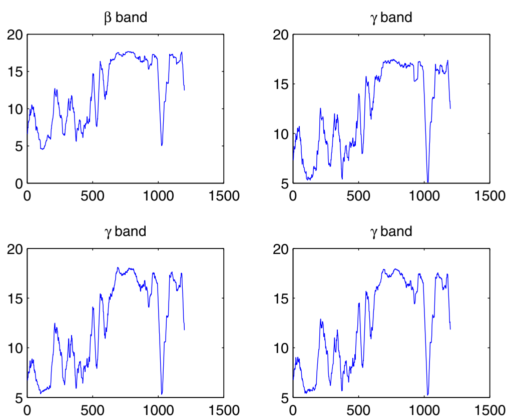

Fig. 4. Wake State Estimation Result over Train Data. Y axis denote the wake degree, while In Figure 3 it denote drowsy degree.

displayed in Figure 5. In Figure 5 we only displayed two estimation result which based on β, λ band frequency energy data. In the above figure, we haven't normalized the Y axis values or given the estimation score instead of the initial calculated data, because we cannot give an appropriate method based on our algorithm framework right now. In our future work, we will committed to solve this problem. In order to further verify the validity of our proposed algorithm, we used the obtained state occurrence and 1-3 order transformation matrixes calculated by the training data to validate the test data, the experiment result are given in Figure 5 and Figure 6. Figure 5 is the fatigue degree and Figure 6 is the wake degree. Comparing Figure 1- the subject's response time and color recognition error rate, we can find that the proposed algorithm can basically estimate the subject's vigilance level. Since only one ICA component is used in the experiment, our algorithm having a good real time capabilities.

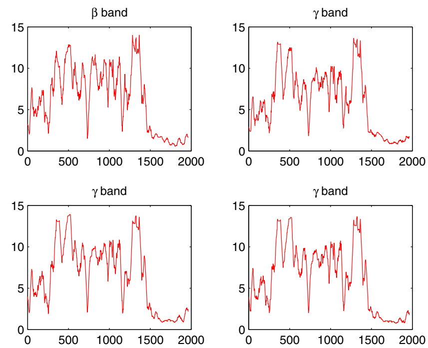

Fig. 5. Estimation Result of Drowsy Degree over Test Data

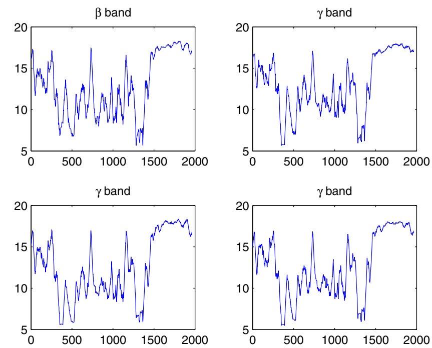

Fig. 6. Estimation Result of Wake Degree over Test Data

5 Conclusion and Future Work

In this paper, we proposed a statistical algorithm for vigilance estimation based on EEG recordings. We use only one ICA component and then extract energy feature of the λ frequency band with Morlet Wavelet. Inspired by the markov model, histogram method is used to compute the wake and drowsy state probability and 1,2 and order transformation matrix. We used one data for template and another for test, the experiment result show that our proposed algorithm frame reliable and effective. Our job is just at an initial stage, more effort should be paid in solving the following problem:

1. More accurate and reliable method for vigilance states division.More accurate and reliable method for vigilance states division.
2. Design better algorithms based on the work and give a more accurate experiment result.
3. More reliable criterion to assess the estimation results based on our algorithm framework.

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