

Vigilance Estimation Based on EEG Signals

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Abstract—In some tasks that require sustained attention, vigilance levels of the operator might become very important. EEG has been proved very effective for measuring vigilance. However, many difficulties exist in this field such as how to label the EEG data, how to remove the noise from the EEG data and so on. In this paper, we introduce a very useful signal transform method, Common Spatial Pattern, to process the EEG data. Also we use unsupervised learning methods for analyzing the EEG data under two extreme cases, sleeping and awake, and discard other middle vigilance states. The results of our experiments are quite promising and give a direction for the vigilance labelling and feature selection in the future work.

I. INTRODUCTION

During the past few decades, studies on vigilance (alertness) have shown that vigilance estimation is very useful to our daily lives. For many human machine interaction systems, the operators should retain vigilance above a constant level. For example, airway dispatchers, pilots and long-distance truck drivers need to retain a high level of vigilance. However, many studies of vigilance research during the past few decades have shown that, for most or all operators engaged in attention-intensive and monotonous tasks, retaining a constant level of alertness is rare if not impossible. As a result, we need a effective method to measure the current vigilance level of the operator.

Previous studies have shown that information regarding alertness and cognition is available in electroencephalographic (EEG) recordings [1][2]. Comparing with other techniques such as face recognition, EEG signals can reflect the vigilance levels much sooner and more accurately. Figure 1 shows the framework of vigilance monitoring system for simulated driving environment. In the figure, EEG signals of the subject are collected and transferred to the computer for analyzing. Then the feedback from the computer is shown on the screen.

In EEG-based vigilance research field, most effort focuses on the evoked potential (EP) response under different vigilance levels [3]-[10]. Recently, the group mean performance of EEG signals under different vigilance levels is used. According to the mean performance during a fixed time period, vigilance

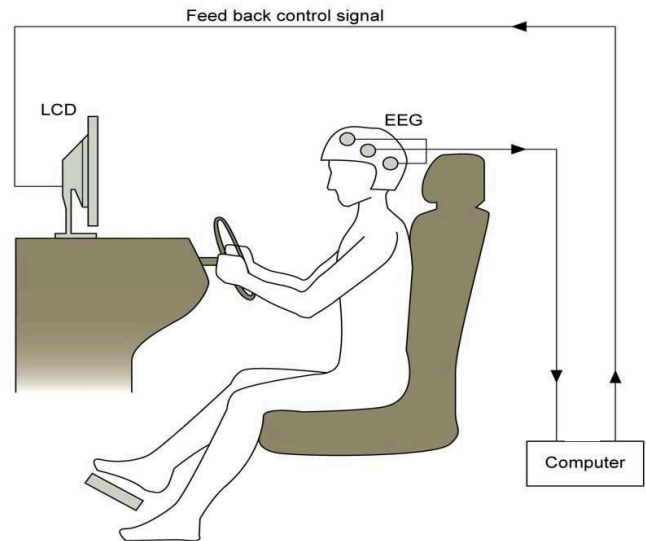


Fig. 1. The framework of vigilance monitoring system for simulated driving environment.

levels can be estimated. Then the relation between EEG and vigilance is analyzed. However, during these vigilance experiments, the time window for calculating the mean performance is usually too long to estimate the vigilance levels in time. Besides, vigilance levels can be estimated according to the power spectral density (PSD) distribution or the energy changes of specific rhythm. Comparing to other methods, these analyzing methods are much more expensive and difficult to implement. The technical challenges involve in estimating vigilance levels using EEG signals include getting enough accurate EEG signals corresponding to each vigilance levels, variations between subjects, sensor characteristics, subject reaction to the environmental sounds and lights, techniques used to analyze the EEG data, and so on.

This research shows that indeed there is relationship between the vigilance level and the EEG signals. Vigilance analysis based on EEG signals is divided into the following four steps [16]. Firstly, obtain large amount of EEG data and the corresponding vigilance levels. Secondly, perform preprocessing to the EEG data such as noise reduction and

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artifacts removal. Thirdly, transform the EEG signals and extract features from these signals. At last, analyze the vigilance levels these signals belong to. The detailed techniques used in this paper are discussed below.

In this paper, we use unsupervised learning methods to analyze the spatio-temporal features of the EEG data and try to differentiate the EEG signals of different vigilance levels. Firstly, we mainly use Common Spatial Patterns (CSP) [11][12] to select the vigilance related features. Then, we use several clustering methods trying to distinguish EEG signals of different vigilance levels. At last we compare and analyze the results of the experiment.

This paper is organized as follows. In section II, the methods used for vigilance analysis are described. In section III, experimental setup and results are presented. Finally, some conclusions are drawn in section IV.

II. METHODS

The whole process in our experiments consists of three main parts. Firstly EEG signals are preprocessed for artifact and noise reduction. We remove the noise caused by the eye blinking and muscle movement and discard other abnormal EEG data. This is achieved by using Editor4.3 from the NeuroScan System. Then related features are extracted, and the appropriate features are selected. Finally, we use several clustering methods such as normalized cut and bipartite graph soft clustering to cluster the data.

A. EEG Preprocessing

Originally, the EEG signals contain a lot of artifacts and unrelated signals. Generally speaking, there are two types of artifacts [13]. The first type is the extra cerebral source artifact which is recorded together with EEG, such as electrooculogram (EOG), electromyography (EMG), and ECG. The second type is the technical artifact resulting from the EEG recording system, such as signal drift and decay.

In our experiments, the 128-channels NeuroScan System SynAmps is used to record EEG signals. The extra cerebral source artifacts mainly consist of EOG and EMG induced by movement. The EOG signals are removed by Scan4.3 software installed in the NeuroScan System. And obvious EMG signals are rejected by hand. For the high performance of the NeuroScan System, the technical artifacts could be ignored except the signal drift which could also be corrected by Scan4.3 software.

B. Feature Extraction and Selection

Besides the artifacts we talked about in the last section, there exist a lot of background signals which are unrelated to vigilance change. So we need a decomposition method which can extract the EEG signals we interested in. As we know, there are a lot of classical or effective decomposition methods. But unfortunately, as the energy of background signals is much greater than the energy of the signals we interested in, most of them are not suitable under this situation. Here we use

Common Spatial Patterns (CSP) [11][12] to extract signals of two distinct vigilance states of the subjects.

CSP can be seen as a variation of Principal Components Analysis (PCA). During the CSP processing, the EEG signals with two different labels are firstly whitened and then projected to the common spatial patterns. After that, the spatial patterns corresponding to the largest difference between the two kinds of EEG signals are chosen as the projection factors. Finally, it uses the projection factors to decompose the EEG signals. An illustration is shown in Fig 2.

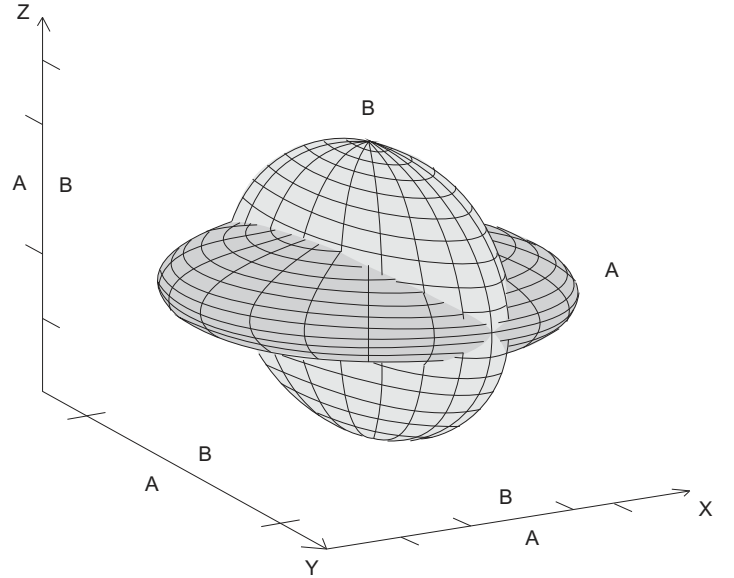


Fig. 2. X, Y, Z denote the common spatial patterns of whitened 2 conditions 3D data, two ellipsoids denotes the variance of two conditions data. The variance of two conditions data is the same on Y , much different on X and Z . So common spatial patterns X and Z should be chosen as the optimal separating projection factors.

CSP projection can be formulated as,

$$Z = PV \quad (1)$$

where V denotes the original signals, P denotes the projection matrix and Z denotes the decomposed signals.

Suppose two kinds of EEG signals are denoted by X_a and X_b , respectively. Both of them are the combinations of events-related signals and background signals.

$$X_a = [C_{a1}, C_{a2}] \begin{bmatrix} S_a \\ S_{c1} \end{bmatrix}, \quad X_b = [C_{b1}, C_{b2}] \begin{bmatrix} S_b \\ S_{c2} \end{bmatrix} \quad (2)$$

where S_a and S_b are the events-related signals, S_{c1} and S_{c2} are the background signals, C_{ai} and C_{bi} are the combination coefficients. Assume that S_{c1} and S_{c2} are the same background signals, then CSP can be used to extract the events-related signals S_a and S_b .

The detailed algorithm is described as follows: Denote the centralized multi-channels EEG signals under two conditions as V_A and V_B with dimensions of K (channels) by L (samples). For convenience, we assume $L > K$. The covariance

matrix of EEG signals under the two conditions can be estimated by

$$R_A = V_A V_A^T, \quad R_B = V_B V_B^T \quad (3)$$

where R_A and R_B are K by K matrices. Then take the sum two covariance matrices as R and factorize it into the product of eigenvectors and eigenvalues,

$$R = R_A + R_B \quad (4)$$

$$R = U \Sigma U^T \quad (5)$$

where U is the matrix of eigenvectors and Σ is the matrix of eigenvalues. The whitening transformation matrix is formed as follows.

$$W = \Sigma^{-1/2} U^T \quad (6)$$

It can be shown that if R_A and R_B are individually transformed as

$$T_A = W R_A W^T, \quad T_B = W R_B W^T \quad (7)$$

then T_A and T_B have the following properties: They share common principal components, and the sum of the corresponding eigenvalues for the two matrices will always be one, i.e.

$$T_A = U_C \Sigma_A U_C^T, \quad T_B = U_C \Sigma_B U_C^T \quad (8)$$

$$\Sigma_A + \Sigma_B = I \quad (9)$$

The above results show that, the variance of the principal components are maximal for condition A and minimal for condition B . So this transformation is optimal for separating the two kind of EEG signals. At last, the CSP decomposition can be expressed as

$$S = P V = U_C^T W V \quad (10)$$

where V is the EEG signals matrix, and S is the matrix of common spatial components.

In order to separate the two kinds of EEG signals optimally, the common spatial components corresponding to large eigenvalues in one condition and small eigenvalues in another condition should be chosen as the projection factors. So the projection matrix should be,

$$P_S = U_{CS}^T W \quad (11)$$

where U_{CS}^T is the selected CSP, and P_S is the final projection matrix.

Many vigilance researches show that for spontaneous EEG signals, vigilance changing is mainly reflected by PSD changing. Figure 3 shows the distribution of EEG energy around 3Hz on the scalp. We can obviously see that the energy changing from clear-headed to sleeping state is quite distinct.

So after CSP transform, we use discrete short time fourier transform to extract the PSD of each CSP projected EEG signals Y and take the PSD bellow $50Hz$ as the feature information with frequency resolution $1Hz$.

$$V_{PSD} = STFT\{Y\} \quad (12)$$

where $STFT$ denotes short time fourier transform, and V_{PSD} is the PSD matrix with dimension $50 \times M$ by N (number of time window).

EEG signals can be divided into the following 5 rhythms [26]:

- δ rhythm 0.5-3.5Hz
- θ rhythm 4-7Hz
- α rhythm 8-13Hz
- β rhythm 14-25Hz
- γ rhythm above 26Hz

From awake state to sleepy state, EEG energy around 13Hz (between α rhythm and β rhythm) will gradually decrease, meanwhile EEG energy around 4Hz (between δ rhythm and θ rhythm) will gradually increase. We choose the signals with energy between 2Hz and 30Hz as features for further analysis.

Then we use PCA to reduce the dimension of the feature matrix,

$$V_R = P_R V_{PSD} \quad (13)$$

where P_R is the matrix of principals spatial patterns with dimension m by $50 \times M$, and V_R is the m by N dimension reduced feature matrix.

C. Clustering

We use several clustering methods such as Normalized cut [14], soft clustering [15] and K-mean to cluster the EEG data.

The algorithm of soft clustering is described briefly as follows. Denote W as the matrix of pairwise data relations with dimension N by N , and B as the matrix of relations between data and clusters with dimension N by k (number of clusters). The relations among V_i can be formed as,

$$\widetilde{W} = (B \Lambda^{-1} B^T), \quad \Lambda = \text{diag}(\lambda_1, \dots, \lambda_k) \quad (14)$$

where $\lambda_j = \sum_{i=1}^N B_{ij}$. If we want to get a optimal estimation of B , the divergence between W and \widetilde{W} must be minimized. To make the problem easy to solve, we replace $B \Lambda^{-1}$ by H . Then the objective function is formed as,

$$\min\{l(W, H \Lambda H^T)\}, \quad \text{s.t.} \quad \sum_{i=1}^N H_{ip} = 1 \quad (15)$$

where $l(\cdot, \cdot)$ is a divergence operator. Let $l(X, Y) = \sum_{i,j} [X_{ij} \log(X_{ij}/Y_{ij}) - X_{ij} + Y_{ij}]$, then the objective function in Equation (15) can be reduced by the following update rules,

$$\tilde{H}_{ip} \propto H_{ip} \sum_j \frac{W_{ij}}{(H \Lambda H^T)_{ij}} \lambda_j H_{jp}, \quad \sum_i \tilde{H}_{ip} = 1 \quad (16)$$

$$\tilde{\lambda}_p \propto \lambda_p \sum_{ij} \frac{W_{ij}}{(H \Lambda H^T)_{ij}} H_{ip} H_{jp}, \quad \sum_p \tilde{\lambda}_p = \sum_{ij} W_{ij} \quad (17)$$

Finally, we get the data cluster relations,

$$B = H \Lambda \quad (18)$$

Then the relation between data and clusters can be seen as the probability that the data belongs to the clusters.

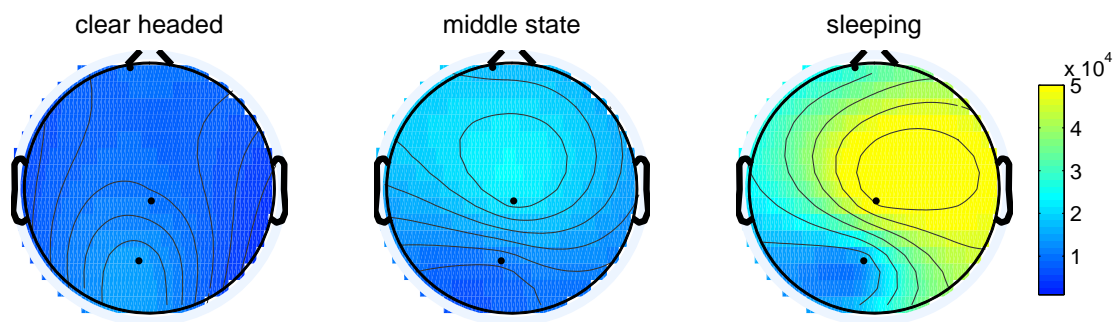


Fig. 3. Distribution of EEG energy around 3Hz on the scalp.

III. RESULTS

The EEG signals we used in our experiment are acquired through the equipment Scan4.3 of the NeuroScan System. The subject wears a special hat with 64 electrodes connected to the amplifier of the NeuroScan system (see Figure 4). He or she lies on the bed in a normally illuminated and insulated room, trying to go to sleep(see Figure 5). The temperature of the room is kept at about 24 degrees and the humidity is kept between 40% and 60%. 64 channels of signals including 4 channels of EOG are recorded. Each experiment lasts about one hour. During the experiment, a period of soft and short music is presented to the subject several times. The music lasts 10 seconds and volume of the music is tuned such that the subject will not be disturbed during the sleeping process. If the subject hears the music which shows that he or she is awake, the subject just opens his or her eyes. If not, the subject keeps on sleeping and it means that he or she falls asleep. We used a DV camera to record the subject's activities. Figure 6 shows the waveforms of original EEG data. The sharp peaks in the figure are probably caused by EMG or EOG. The EEG signal around the time when the music is played is discarded.

In our experiments, 20 channels of EEG data recorded from electrodes located at the center of the head are used. The distribution of electrodes is shown in Figure 7. Electrodes are arranged based on extended 10/20 system.

Short-time Fourier Transform is used to transform the results of the CSP transform to the frequency field. We choose the EEG signals of frequency between 2Hz and 30Hz to analyze. Then PCA is used to reduce the dimensions. The main results of these methods are shown below. We select the EEG data when the subject is completely awake or sleeping and discard other data when the vigilance level of the subject is in between. Then K-mean, Normalized-Cut and soft cluster are used to cluster the EEG data in different situations. We make a decision on the current vigilance state of the subject every 4 seconds.

Figure 8 shows the results of clustering the original EEG data directly using K-mean, normalized-cut and soft cluster. Figure 9 shows the results of clustering the data after CSP transform and feature selection. From these figures, we can easily find that CSP transform could greatly increase the accuracy of the clustering. Also soft cluster outperforms the



Fig. 4. The subject wears a special hat with 64 electrodes connected to the amplifier of the NeuroScan system. The four electrodes attached to the face of the subject are used to record EOG.



Fig. 5. The environment of our experiments. The subject lies on the bed in a normally illuminated and insulated room, trying to go to sleep.

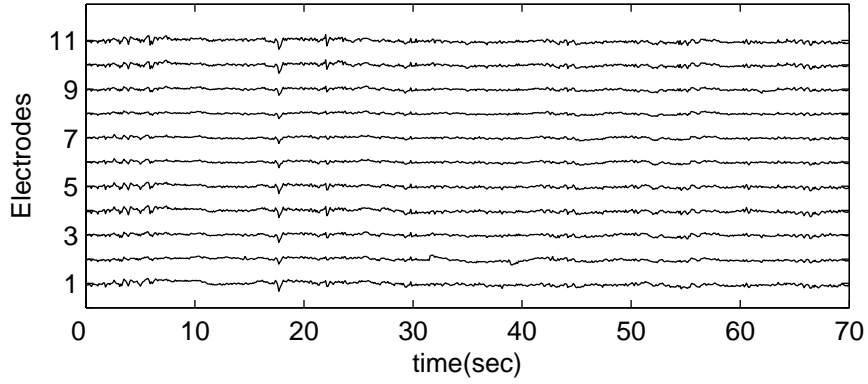


Fig. 6. The shape of the original EEG data. The sharps in the signal are probably caused by EMG or EOG.

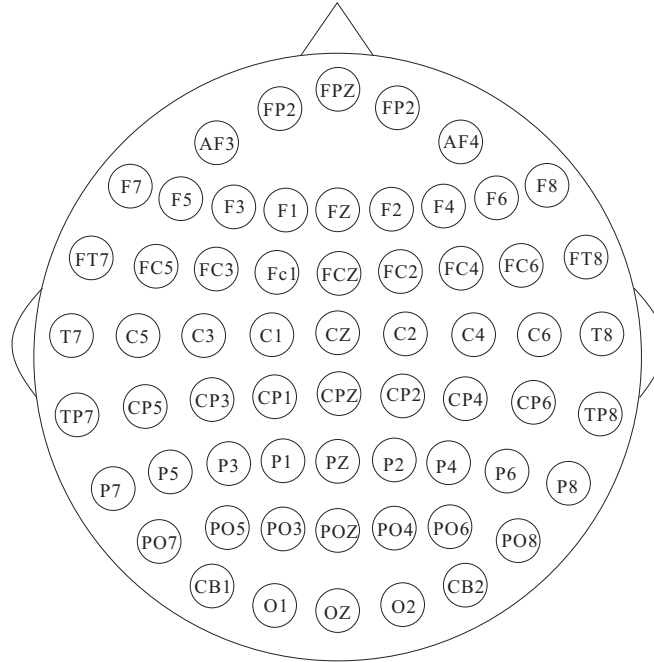


Fig. 7. Electrodes distribution of extended 10/20 system. Totally 64 channels of EEG signals are recorded. We use 20 channels located in the center of the head to analyze.

other two clusters a bit.

Figure 10 shows the results of clustering the EEG data into three levels of vigilance.

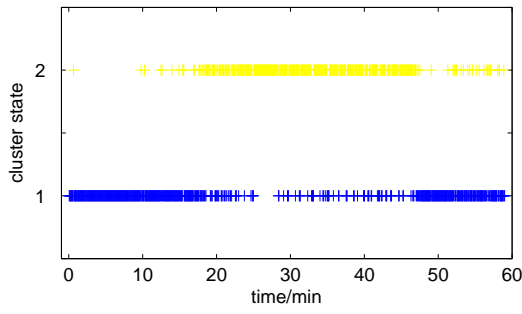
IV. CONCLUSION

In this paper, we analyze the EEG data and extract features corresponding to two distinct vigilance levels: awake and sleeping, and avoid the middle levels. Also we introduce common spatial pattern and other signal processing methods to analyze EEG data for the vigilance estimation. From Figure 9 we can see that the two extreme states, sleeping and awake, can be discriminated precisely. From Figure 10, even different sleeping levels can be described to some extent. The level two and three can be seen as different waking levels. As a result, common spatial pattern and the power spectrum analysis can be good tools for analyzing the EEG signals.

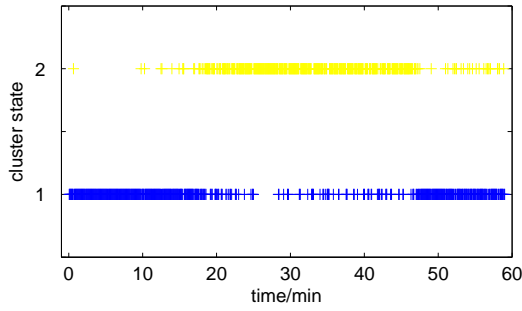
Previously, researchers only analyzed the statistical relationship between the vigilance state and the EEG signals. In this paper, we use unsupervised learning method to analyze the EEG data of two extreme cases and discard other middle vigilance states in order to discover the distribution of the EEG data by using spatio-temporal filters and signal decomposition methods. This paper reports our preliminary results for estimating different vigilance levels with EEG signals. The results are quite promising and give a direction for the vigilance labeling and feature selection for the real time vigilance estimation system in the future.

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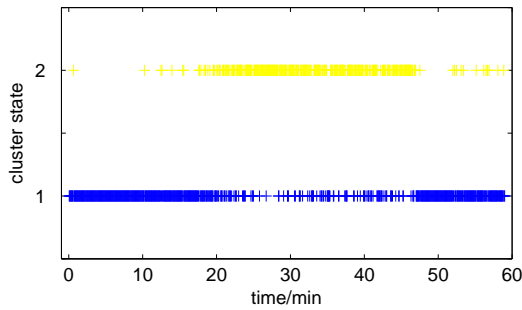
We would like to thank the volunteers for taking part in our vigilance experiments and also special thanks to Zhong-



(a)

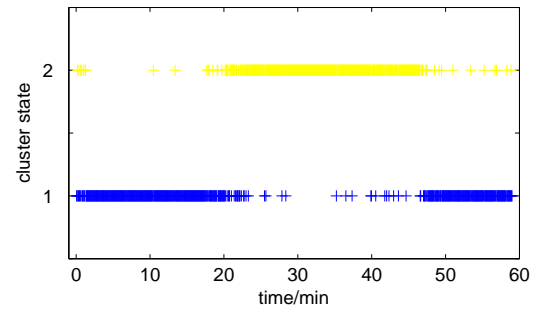


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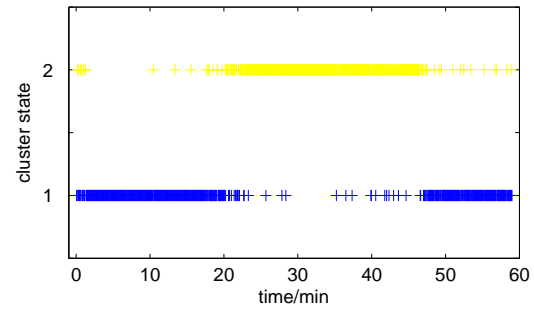


(c)

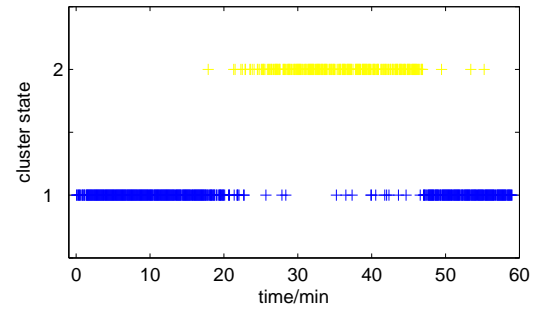
Fig. 8. Cluster the original EEG data into two levels using (a) K-Mean algorithm, (b) Normalized-Cut algorithm; (c) Soft clustering algorithm. X-axis represents the time and Y-axis is the vigilance levels. The top line stands for the sleeping state and the bottom line stands for the waking state.



(a)



(b)



(c)

Fig. 9. Cluster the PSD of the data after CSP transform using (a) K-Mean algorithm, (b) Normalized-Cut algorithm; (c) Soft clustering algorithm. X-axis represents the time and Y-axis is the vigilance levels. The top line stands for the sleeping state and the bottom line stands for the waking state.

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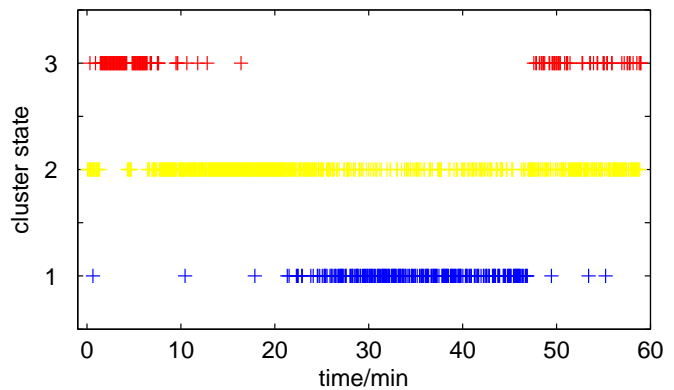


Fig. 10. Cluster EEG signals into three levels. The level one stands for the sleeping state while level two and three can be seen as different waking levels.

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