EEG-based Brain Computer Interface for Vigilance Analysis and Estimate

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Abstract—Monitoring vigilance is most important to prevent many accidents caused by the decline in the operator’s alert. Since electroencephalogram (EEG) is the recording of electrical activity in the brain, it is assumed as one of the most reliable physiological indicators for vigilance. In this paper, a EEG-based brain computer interface (BCI) system is proposed for vigilance analysis and estimate, which establishes vigilance model using EEG data changing from wakefulness to drowsiness, estimates the vigilance level by correlation analysis, and visualizes multi-modal EEG characteristics to help to reveal and understand the dynamic features of EEG in different vigilance levels.

Experiment results show that the vigilance level could be ranked and estimated reasonably in the proposed system. Therefore, it has implications for developing the practical EEG-based vigilance monitor device.

I. INTRODUCTION

Retaining a constant level of vigilance is vital in performing monotonous but attention demanding task, such as mechanical operating and vehicle driving. Monitoring vigilance will be extremely useful to prevent many accidents caused by the decline in the operator’s alert. It is known that various physiological factors have been proposed to detect vigilance, such as eye activities, heart rate variability (HRV), skin electric potential, and particularly, electroencephalographic (EEG) [1-3]. EEG is the recording of electrical activity produced by the firing of neurons within the brain, therefore it contains the most objective brain state information, and is assumed as one of the most reliable indicators of vigilance[4]. Studies show that the changes in EEG spectrum related to the vigilance state, and a number of methods have been proposed to make accurate judgments of vigilance levels[5-9]. However, building up a EEG-based vigilance monitor device easy to apply is still challenging.

In this paper, a EEG-based brain computer interface (BCI) system is proposed for vigilance analysis and estimate, which establishes vigilance model using EEG data changing from wakefulness to drowsiness, estimates the vigilance level by correlation analysis, and visualizes multi-modal EEG characteristics to help to reveal and understand the dynamic features of EEG in different vigilance levels.

The rest of the paper is organized as follows. The proposed BCI system architecture is introduced in Section 2, Section 3 describes the method for vigilance analysis and estimate. Experiment setup and results are presented in section 4. Section 5 offers the conclusion.

II. SYSTEM ARCHITECTURE

The General framework of the developed EEG-based BCI system is illustrated in Fig.1: multi-channels raw EEG signals are first collected as inputs, and then EEG signal must be denoised and removed artifacts. After the preprocessing of EEG data, vigilance level would be analyzed by feature extraction and pattern classification algorithms, the results would trigger the warning device when the drowsiness condition occurs. Especially, multi-modal EEG visualization module provides the characteristics of the current signals over frequency domain and space domain to present intuitive interpretation of vigilance feature in EEG signals. System setting module controls all of functional processes, such as the parameters in signal preprocessing, the options for visualization and the vigilance scale setting.

III. METHOD

The detail description of the method to analyze and estimate the level of vigilance is shown in Fig.2. Raw 62 channels EEG data are first preprocessed using a simple low-pass filter with a cut-off frequency of 40 Hz to remove the line noise and some high-frequency noise. Then the Principal Component Analysis (PCA) is applied to reduce the 62 channels data to 26 principal components. Due to the close relationship between the EEG spectrum and the subject’s vigilance state, the rhythm activities, that is, EEG power in the four specified bands, δ(0-4 Hz), θ(4-8 Hz), α(8-13 Hz) and β(13-30Hz) and their ratios, which are θ/β, α/β, θ + α/α + β, and θ/β, are calculated as features for vigilance detection. For each obtained PCA component, the rhythm activity features are calculated based on Fast Fourier Transform (FFT) algorithm.

According to [10,11], the vigilance state transform during a long term is a gradual changing process, and the wakefulness...
to sleepiness are the ultimate vigilance levels. Therefore, the
discriminative feature between the two ultimate states could
be selected as vigilance indicated feature. For each individual
feature of each PCA component, its fisher score is computed,
and then PCA components with the large Fisher scores are
retained as the significant PCA components, and correspond-
ing features are taken as the selected features. Fisher score
is utilized to eliminate redundant indiscriminative features,
and more details could be found in [7]. Next, the vigilance
model could be derived by clustering method, which has been
successfully used to distinguish other middle states between
wakefulness and sleepiness [8]. In the vigilance estimate stage,
the vigilance level could be calculated by correlation analysis
with the established vigilance model.

IV. EXPERIMENTS AND RESULTS
A. Experiment set up

In order to acquire EEG data in different vigilance states,
including the wakefulness and sleepiness, experiments have
been carried out in the Lab for Brain Cognition and Intelligent
Computing, Tong Ji University, China. Subjects were required
to lie on a bed with eye closed and body relaxed. 62 channels
of EEG signals, located at standard positions of the 10-20
international system, were recorded by an ESI-128 channel
high-Resolution EEG/EP systems (SynAmps2, Neuroscan).
Since each experiment was taken after lunch, most of subjects
would gradually get drowsiness even fall into a sleep rapidly.
With the same technique as in [8], the wakefulness state and
sleepiness state were labeled by the feedback information
from the subject and combine with the experiment video
record. Totally, thirteen healthy male subjects, aged from 21
to 30, took part in the experiments, and nine session EEG
data including wakefulness-sleepiness-wakefulness states are
acquired at last. EEG signals were recorded, sampled at 250
Hz and bandpass filtered between 0.1 Hz and 40 Hz, and 5s
time window was applied in the following calculation.

B. Results

By fish score, the discriminative PCA components are se-
lected, and the corresponding features are taken as significant
indicators for vigilance level. For most subjects, those fea-
tures present significant differences between wakefulness and
sleepiness states. It is demonstrated that PCA algorithm could
improve the classification results in [7]. In Fig.3 and Fig.4,
for a typical subject, averaged EEG band power and ratio features
in this two states is illustrated by being projected back into the
brain topography. It is obvious that slow wave activitie (δ, θ)
increase, fast wave activitie decrease (α, β), and the ratio
of slow wave to fast wave EEG activities increase while the
vigilance level switch from wakefulness into sleepiness. The
features are extracted by the proposed feature calculation and
selection, and the best ratio features are mostly found in δ, θ
+α/α +β in the frontal cortex, the δ , α, α/β, θ+α/α +β in
the temporal cortex, $\delta$, $\alpha$, $\alpha/\beta$ and $\theta/\beta$ in the parietal cortex, and $\beta$, $\theta/\alpha$ in the occipital cortex, which are consistent with many physiological studies. Those selected features would be taken as vigilance indicators next.

Fig. 3. Brain topographies of averaged EEG band power features, $\delta$ (0.1-4 Hz), $\theta$ (4-8 Hz), $\alpha$ (8-13 Hz) and $\beta$+ (13-40Hz) in different state. The first row is in wakefulness state, the second row is in sleepiness state, and the bottom stands for the difference between two states.

$$\frac{\theta + \alpha}{\beta +} \quad \frac{\alpha}{\beta +} \quad \frac{\theta + \alpha}{\beta +} \quad \frac{\theta}{\beta +}$$

Fig. 4. Brain topographies of averaged ratio features, $\theta/\beta$, $\alpha/\beta$, $\theta/\beta$ and $\theta/\beta$ in different state. The first row is in wakefulness state, the second row is in sleepiness state, and the bottom stands for the difference between two states.

Based on the selected features, a popular clustering method, Gaussian mixture model-based (GMM) clustering, is applied to assess a gradual changing process, and obtain a vigilance model. Experiment results show that the cluster method can not only distinguish wakefulness from sleepiness, but also identify reasonable middle states. Fig.5 illustrates cluster results for about thirteen minutes’ EEG data, acquired from wakefulness into sleepiness.

With derived vigilance model, the vigilance level could be estimated by correlation analysis. Fig.6 presents vigilance estimate results for EEG data acquired during a wakefulness-sleepiness-wakefulness period. Based on the vigilance model calculated in training stage, the vigilance levels in testing stage are ranked reasonably.

Visualization of vigilance indicated features provides more intuitive interpretation of the relation between the vigilance level and EEG characteristics. Fig.7 shows the part of visualization interface in the proposed BCI system. The timing sequence of multi-channel EEG data are displayed, which help to inspect whether artifacts have been filtered out. The rhythm activity features are visualized in histograms to present the changes of EEG spectrum directly, and the corresponding brain topographies (the rhythm activity feature projection) are given to indicate the corresponding brain region. At the same time, the estimate results of vigilance level are listed. Simulation shows that the multi-modal EEG visualization is effective to reveal and understand the dynamic features of EEG in different vigilance levels.

Fig. 6. vigilance estimate results for EEG data acquired during a wakefulness-sleepiness-wakefulness period. The left, right panels denote classification results of three, four vigilance states respectively. The broken line denotes the partition between the training data and testing data.

Fig. 7. Multi-modal EEG visualization in the proposed system.

V. CONCLUSION

In this paper, a EEG-Based brain computer interface system for vigilance analysis and estimate is proposed. Firstly, vigilance model is derived using the EEG data changes from wakefulness to drowsiness, and then the vigilance level could be ranked and estimated reasonably by means of correlation analysis with the vigilance model. Moreover, multi-modal EEG characteristics can be visualized to reveal and understand the dynamic features of EEG in different vigilance state.
Fig. 5. Clustering results for about 13 minutes EEG data acquired from wakefulness to sleepiness. The left, middle, right panels denote the clustering results of two, three, four vigilance levels respectively.

Experiment results suggest that with vigilance model, the vigilance could be estimated for real-time application. The proposed system has implications for the developing practical EEG-based vigilance monitor device, which can greatly reduce accidents caused by the decline in the operator’s alert.

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