EEG Pattern Recognition — Arousal States Detection and Classification

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ABSTRACT

In this paper, we use electroencephalogram (EEG) to detect the arousal states of human. The EEG patterns fluctuating between waking and sleep are described as several features extracted from the moving time windows. The significant feature, mean frequency (MF), is used for arousal states detection.

The fluctuations of the EEG mean frequency are characterized as Hidden Markov Models (HMMs), which well estimate the next possible arousal state. In this HMM, single current-to-next state transition probability is considered along with global states transitions. Both local contextual effects (LCE) and global contextual effects (GCE) autoregressive HMMs are used to estimate and detect the transitions from waking to sleep. The validity of our proposed model is verified via a behavior measure – the correct rate of the subject's responses to auditory stimuli. In our study, the estimated values of mean frequency by GCE HMM show high correlation with the behavior measure. This high recognition rate makes arousal states detection practicable. Furthermore, the LCE HMMs are also applicable for artifacts rejection.

In real-time arousal states detection, alarms are given whenever the subject's vigilant states turn into drowsy states. This system has many applications, for example, it can be used to maintain long term vehicle driver's arousal.

1. Introduction

One of the most likely causes of vehicle accidents is drivers' falling asleep at the wheel [1]. During a long term driving, drivers become fatigable and drowsy. They need to be warned to take a rest before drowsiness taking over. On the other hand, the alertness of operators working at night in nuclear power plants must be well maintained [2]. Drowsiness may induce error responses of the operator to immediately decision-making work. Accidents due to those error responses would involve tremendous disasters. Thus, the necessity to design a system assuring alertness on one's watch cannot be over emphasized.

Fluctuations of electroencephalogram (EEG), representing global activities of brain cells, are applicable for arousal states detection. EEG can be recorded via electrodes placed on human scalp. From waking to sleep, EEG varies in frequency bands ranging from beta waves (13-30Hz) to alpha waves (8-12Hz), and successively to theta (4-8Hz) and delta (0-4Hz). Long term sleep stages are well defined according to Rechtschaffen and Kales (R+K) criteria [3]. Recent studies [4, 5] have shown that the transition from active waking to sleep onset (stage 1) could be divided into at least three substates according to EEG patterns or behavior measures. However, EEG significance of such transition is still poorly defied. Thus, we intend to obtain an eminent EEG feature by examining the relationship of several EEG features to behavior arousal and to establish a valid procedure of EEG feature analysis for arousal states detection, especially in the transition from waking to drowsiness (or sleep onset). On the other hand, the time scales manually used to judge sleep stages are always minute-scales. With minute-scales, the fine changes intervening between minutes will not be shown. Since it is very likely that accidents may occur within seconds, the time intervals/windows for the detection of arousal states should be selected as short as possible.

Many ways to extract features from a segment of the raw EEG data have been proposed. In time domain, average value of EEG amplitude, standard deviation, energy (sum of squared EEG amplitude) are evaluated[6]. In frequency domain, energy contents of each band (beta, alpha, theta, and delta) are used[6]. Mean frequency (MF), the center of gravity of the EEG spectrum, is also evaluated [6, 7].

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Moreover, autoregressive moving average model (ARMA) coefficients [8, 9], including Kalman filter [10], as well as power spectrum estimation (PSE) [12] are other possible approaches to extract EEG features. Among them, some features show little correlation with drowsiness; some show redundancies with other features; some require high order computational power that are inapplicable to real-time processing. To solve these problem, features are selected on the presupposition that they are most significant in arousal states, and least in computation and redundancy.

Previous studies of neural networks for classification of sleep stages have been developed such as "back-propagation" [6], "feedforward" [11], and "self organization map"(SOM) [10]. They may well classify the long term sleep EEG into several stages. However, most of them are off-line, and static analyses without considering the dynamic state-to-state transitions, especially for waking-sleep patterns. Those static analyses are unable to estimate the EEG dynamics in terms of contextual effects, and be applied to real-time arousal states detection.

Hidden Markov Models (HMMs) [17], well-known in speech recognition, can be applied to EEG for estimating the trend to drowsiness. In the present study, we use HMM to characterize the fluctuations of EEG MFs. The transition probabilities of MFs are evaluated to establish a HMM. HMMs are valid under the assumption that the human physiological states change gradually with finite state transitions. Artifacts resulting from muscular activities may cause abrupt and unexpected state transitions [16], which invalidate the HMMs. Furthermore, subjects with epilepsy [13] or sleep disorders may cause instability to the HMMs. In our experiment, subjects should be normal adults, and free from caffeine, alcohol, and drugs in order to make sure that their normal sleep patterns are maintained.

2. Methods

2.1. Data Acquisition

In our laboratory, BIOPAC MP100WS Data Acquisition System (Acq), was used to acquire raw electro-physiological signals , and these signals were stored simultaneously in hard disk for later post-acquisition analysis. A 10-20 electrode cap (for EEG) was fitted to the subject's skull, two EOG electrodes were placed on left and right canthus each, and two EMG electrodes were placed on the chin. The sampling frequency was 64 Hz, and the gain of the amplifier was 10000. A V8 camera was also used to monitor the subject's behavior without interruption.

2.2. Experimental Design

The subject was asked to response to tones randomly presented by pressing a button. The tones was 1000 Hz with 50 ms duration. It was 2dB louder than background noise (50 dB), and appeared randomly with 3 to 8 seconds "inter-stimulus interval" (ISI). Correct rates (CR) defined as the ratio of responded tones to total number of tones in 32 secs were evaluated. Correct rates are behavior measures of arousal states [12]. When the subject is getting drowsy, he presses the button with longer reaction time (RT), or totally lapses of the stimuli for a while.

2.3. Off-line, Post-Acquisition Analyses

Firstly, the raw EEG data recorded by *Acq* were transformed into text form, and then analyzed by C programming. Single channel EEG (C_3 vs C_4) was analyzed. EEG data were segmented into consecutively shifting 32-sec time windows which advance every 4 seconds (with 28-sec overlap.)

2.3.1. Feature Extractions:

Time and frequency domain approaches are used for feature extraction. For time domain analysis, standard deviation, energy, and average value of EEG amplitude in each time interval are evaluated. For frequency domain analysis, N-pt FFT is performed for each time interval. The energy contents of beta, alpha, theta, and delta bands are evaluated. The ratios of each band to the total spectrum energy are also calculated. MF , the center of gravity of the EEG spectrum, is defined as:

$$MF = \frac{\sum_{i=1}^{n} f_i M_i}{\sum_{i=1}^{n} M_i} \tag{1}$$

where M_i is the absolute value on the ith frequency f_i (i=1 to N) on the FFT spectrum. In total, we have a 8-D feature vector for each time interval.

2.3.2. Feature Selection

Backward elimination processes of multiple regression analysis were used to select the most significant EEG features (independent variables.) The correct rates (CR) served as the dependent variable in the regression processes.

2.4. Hidden Markov Models

Of all the features, MF shows highest correlation with subject's behavior measure in 32-sec window. Therefore the fluctuations can be used for arousal states detection. MFs show local variations in second-scale and global variations in minute-scale. Evaluating MFs in 4-sec time interval reveals the subject's instantaneous (local) brain activity (Fig. 2, Channel 3) However, the local variations of 4-sec MFs cannot reveal the inherent global arousal states transition. A local decrement or increment of MF does not stand for arousal changes. Local MFs are often corrupted by noises and artifacts. On the other hand, MFs in 32-sec shifting windows do correlate with subject's arousal, however, when an artifact takes place, its effects last when the 32-sec window move across it. (Fig. 2, Channel 2) Furthermore, repeated calculation of the overlapping information is redundant. Therefore, we propose a model that estimates global state transitions from local 4-sec variations, i.e. the actual arousal transitions are hidden in the local variations.

2.4.1. Local Contextual Effects (LCE)

First Order Markov Chain: MFs in 4-sec moving time windows without overlap are evaluated. The fluctuation of MFs is regarded as an observation sequence following a first order Markov chain[17]. MFs are first quantized into 32 discrete states, S_i where $1 \leq i \leq 32$, with equal spaces from 4 Hz to 12 Hz. Then, the transition probabilities of current-state to next-state are evaluated to form a 32×32 matrix $\mathbf{A}$. In this matrix, each element $a_{i|j}$ is defined as follows:

$$a_{i|j} = P[q_t = S_j | q_{t-1} = S_i] \tag{2}$$

where $a_{i|j}$ is the transition probability from state i to state j, S_j is the state at time q_t, and $1 \leq i, j \leq 32$. In addition, the initial state probabilities π_i is defined as:

$$\pi_i = P[q_1 = S_i] \qquad 1 \leq i \leq 32 \tag{3}$$

Autoregressive HMMs: To model the fluctuation of MFs with "second-scale," we establish a 4th order AR-HMM in terms of local 16-sec contextual effects:

T-16s T-12s T-8s T-4s T T+4s
+————-+————-+————-+————-||————-+
MF_{n-4} MF_{n-3} MF_{n-2} MF_{n-1} MF_n

At an instancy T, 4 MFs (MF_{n-4}, MF_{n-3}, MF_{n-2}, and MF_{n-1}) of four consecutively shifting 4-sec time windows before T are used to estimate the MF_n of the next time window:

$$MF_n = \sum_{i=1}^{4} a_i MF_{n-i} + W_n \tag{4}$$

where a_i is the ith coefficient of ARMA, W_n is the error term.

2.4.2. Global Contextual Effects (GCE)

The fluctuations of local MFs within 16 secs may not well estimate the tendency from waking to drowsiness. Therefore, we estimate it in terms of global contextual effects with "minute-scale" or "sub-minute-scale." The 4-sec MFs in a minute-scale window, W, are processed:

$$GMF_n = \sum_{k=n-(p/2)}^{n+(p/2)} a_k MF_k + W_n \tag{5}$$

where p is the number of 4-sec MFs in W , a_k is the kth coefficient, and GMF_n is a global MF value in W. In the present study, each a_k is set to 1/p .

3. Results

3.1. Experimental Results

In this experiment, the subject reported that he did feel drowsy and doze off several times during the task (Fig. 1.) The lapses of responses in Fig. 1 were very likely due to the subject's drowsiness. As shown in Fig. 2 (channel 2,) when the subject began to ignore the tones, there was always a decline of MF. The relation coefficients between "correct rate"(Ch1) and "MF of 32s"(Ch2) in Fig. 2 was high. However, the MF of 32s was very likely corrupted by artifacts (at about 16 mins in Fig. 2.) Therefore, modified global MFs from 4-sec epoch local MF were calculated. The relation between Ch1 and Ch4 is higher than the original MF in 32s, and artifact effects were eliminated.

3.2. The HMMs

First Order Markov Chain: The transition probabilities 32×32 matrix $\mathbf{A}$, defined in Equation (2), of the states of the quantized MFs is evaluated. Preliminary analysis showed that most of the transition probabilities located in the diagonal band of $\mathbf{A}$, and few took place in off the diagonal band. The average vertical width of the diagonal band is about 12 states, which corresponds to a range of 3 Hz. In other words, at an instancy, the quantized MF may change within ± 1.5 Hz. On the other hand, the average value of the absolute difference between two consecutive mean frequencies is 0.91 Hz. All this suggests that the MF in 4-sec interval varies in a restricted range. Abrupt and unexpected states transitions are likely due to muscular artifacts.

Local Contextual Effects AR-HMM: We used four consecutive MFs in 16 secs to estimate the next possible value, MF', and compare it with the observed value of MF. About 75% of deviations between MF' and MF are below 1 Hz. The average deviation was 0.82 Hz, and the root-mean-square (RMS) value is 1.28Hz. Therefore, when the difference between the estimated value and the observed value is more than 2 times the RMS value, the observed value is regarded as an artifact.

Global Contextual Effects AR-HMM: The contextual MFs of 32 secs provide global information that shows the subject's tendency to drowsiness. From simulation, GCE ends up a correct decision of drowsiness with more than 70% rate. On the other hand, the mean frequency related to the critical instancy when the subject totally lapse from responses is about 10 Hz. Therefore, if the estimated value is below 10 Hz, we may say that the subject is getting drowsy.

4. Discussion

The high recognition rate suggests that mean frequency is applicable for arousal states detection. A higher recognition rate is expected if the effects of all system parameters, such as noise and artifact, are eliminated.

In practice, decisions are made based on LCE and GCE every 4 secs. In other words, at an instancy, both local and global contextual EEG before this instancy are combined to estimate the possibility of drowsiness. In this way, alarms can be given every 4 secs without longer waiting. General speaking, 4 secs will be enough to avoid an accident.

The studies of more effective LCE and GCE is ongoing. And we are currently examining the reliability of our models by repeated measures in the same subject. We will also examine our models between subjects for practical applications.

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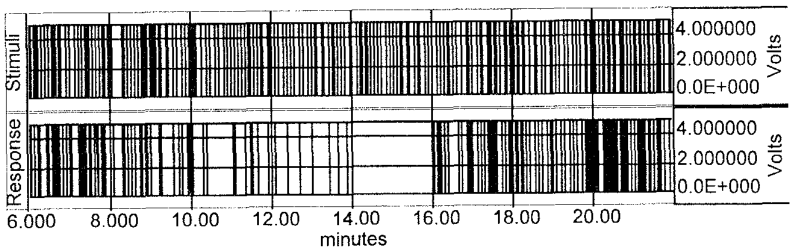

Fig. 1 Record of Subject "A"

First channel: Auditory Stimuli, Second channel: Subject's Responses

The subject didn't response at all from 14 to 16 mins.

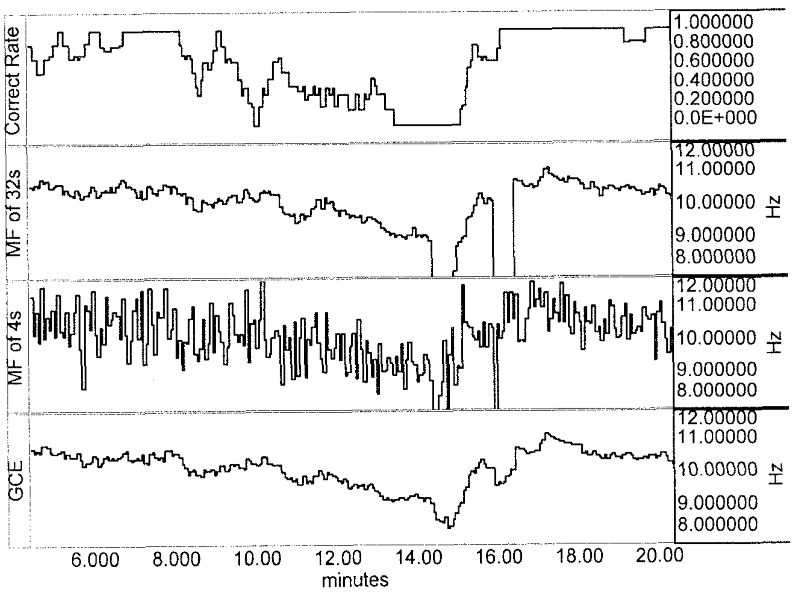

Fig. 2 Subject "A"

First channel (Ch1): Subject's correct rates

Second channel(Ch2): Mean Frequency of 32s shifting time windows

Third channel (Ch3): Mean Frequency of 4s time windows

Fourth channel (Ch4): Modified Mean Frequency in 32s windows by GCE

Relation coefficients: R(Ch2, Ch1)=0.585

R(Ch3, Ch1)=0.553

R(Ch4, Ch1)=0.818