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EEG-based estimation of mental fatigue by using KPCA–HMM and complexity parameters

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ABSTRACT

Two complexity parameters of EEG, i.e. approximate entropy (*ApEn*) and Kolmogorov complexity (*Kc*) are utilized to characterize the complexity and irregularity of EEG data under the different mental fatigue states. Then the kernel principal component analysis (KPCA) and Hidden Markov Model (HMM) are combined to differentiate two mental fatigue states. The KPCA algorithm is employed to extract nonlinear features from the complexity parameters of EEG and improve the generalization performance of HMM. The investigation suggests that *ApEn* and *Kc* can effectively describe the dynamic complexity of EEG, which is strongly correlated with mental fatigue. Both complexity parameters are significantly decreased ($P < 0.005$) as the mental fatigue level increases. These complexity parameters may be used as the indices of the mental fatigue level. Moreover, the joint KPCA–HMM method can effectively reduce the dimensionality of the feature vectors, accelerate the classification speed and achieve higher classification accuracy (84%) of mental fatigue. Hence KPCA–HMM could be a promising model for the estimation of mental fatigue.

1. Introduction

Mental fatigue is a common physiological phenomenon, and is inevitable for office workers in general, which affects the individual's life quality on different aspects. It is usually accompanied with a sense of weariness, reduced alertness, and reduced mental performance, which would lead the accidents in life, decrease productivity in workplace and harm the health. When people become fatigued, they usually experience difficulties for maintaining task performance at an adequate level [1]. In industry, many incidents and accidents are related to mental fatigue as the result of sustained performance [2]. It is important to manage and cope with mental fatigue so that workers do not harm their health. Therefore, the management of mental fatigue is important from the viewpoint of occupational risk protection, productivity, and occupational health.

To date, many methods have been proposed to estimate the mental fatigue. A large number of previous studies use behavioral indices or subjective measures such as reaction time, error ratio or subjective scales. A recent tendency in ergonomic research is to choose more objective measures to assess the mental fatigue state. These approaches focus on measuring physiological changes of people, such as the electrooculogram (EOG), respiratory signals, heart beat rate, skin electric potential, and particularly, electroencephalographic (EEG) activities as a means of detecting the mental fatigue states [3,4]. Although numerous physiological indicators are available to describe an individual's mental fatigue state, the EEG signals may be the most promising, predictive and reliable one [5,6]. The EEG is widely regarded as the physiological "gold standard" for the assessment of mental fatigue.

In present, many scholars have studied the mental fatigue induced by one single task, such as driving task, hypoxia, etc. S.K.L. Lal investigated the use of EEG as a fatigue countermeasure during driver fatigue [7]. C. Papadelis et al. used the nonlinear electroencephalography parameters, i.e. approximate entropy to assess hypoxia-induced EEG alterations, and found these complexity parameters can assess the different hypoxic levels reliably and effectively [8]. B.T. Jap used EEG spectral components to study the EEG activities change during a monotonous driving session [9]. C. Papadelis used the Shannon entropy, the Kullback–Leibler entropy and the cross-approximate entropy to analyze the EEG data from sleep-deprived subjects exposed to real field driving conditions, and found these EEG parameters can assess effectively the brain activity alterations that occur a few seconds before sleeping/drowsiness events in driving [10,11]. However, mental fatigue is a complex phenomenon and it is affected by many factors. Thus, in order to study the sensitivity of nonlinear complexity parameters to different types of mental fatigue, we have first designed three different cognitive tasks to induce three

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different types of mental fatigue, and then used the nonlinear complexity parameters to analyze different type of mental fatigue.

In this study, two complexity parameters, i.e. approximate entropy (*ApEn*) and Kolmogorov complexity (*Kc*) are used to quantify the complexity and irregularity of EEG data under two mental fatigue states, i.e. one before performing a 2-h mental task, and one after. For comparison, Tsallis entropy (*TE*) is also employed to analyze the change of mental fatigue [16]. Then we propose a novel scheme of training Hidden Markov Model (HMM) for estimation of mental fatigue using the complexity parameters in five frequency bands of EEG. Considering the high-dimensionality and nonlinear nature of EEG data [12–15], the kernel principal component analysis (KPCA) is adopted to extract nonlinear features from the complexity parameters of EEG, and then to train the HMM. Thus, KPCA and HMM are combined to differentiate two mental fatigue states. Compared with previous studies, the presented comprehensive methods would make the mental fatigue estimation much more reliable and accurate since many methods are combined.

2. Materials and methods

2.1. Subjects

Fifty male right-dominated graduate students, between 20 and 27 years old ($M = 23.0$ years, $SD = 1.6$), participated in this study. Personal data (handedness, past medical history, medical family history, etc.) were acquired with a standardized interview before EEG recordings. All subjects were in good health. None of them reported on any cardiovascular disease or neurological disorders in the past or had taken any drugs known to affect the EEG. Subjects did not work night shifts and had normal sleep time. All of them were accustomed to use the computer mouse and agreed to join the study.

2.2. Experiment and data acquisition

The experimental tasks were three types of simple cognitive tasks. The first type of task was a vigilance task. Three random numbers displayed at the same time on the CRT screen and changed once every second randomly. The subjects were asked to click the right mouse button promptly, as three different odd numbers, such as 1, 7, 9, appeared. Sixteen subjects participated in this experiment. The second type of task was the addition and subtraction arithmetic calculation of four one-digit numbers. They were displayed on a computer monitor continuously until the subject responded. The participants solved the problems firstly, and then decided whether the result was less than, equal to, or greater than the target sum provided. Sixteen subjects participated in this experiment. The third type of task was a simple switch task. A white square, subdivided into four subsquares, was displayed continuously at the screen center. Stimulus images were presented in turn, and the image was starting from the upper left subsquare with clockwise fashion. The stimulus images were number from zero to nine randomly. The color of the stimulus images was red or blue randomly. Then the subjects should pushed the left or right mouse button related to the image color, respectively, when the stimulus image appeared in either of two upper subsquares, or related to the odd or even number identity if the stimulus appeared in either of two lower subsquares. Eighteen subjects participated in this experiment. All subjects performed the cognitive task until either they quitted from exhaustion or 2 h elapsed. The response time and the number of error trials, if any, were recorded.

Subjects were required to abstain from alcohol and caffeine-containing substances 24 h before the experiment. Subjects were told the study was aimed at investigating the neural correlates of cognitive control, they were unaware the study was about mental fatigue. To avoid the influence of circadian fluctuations on subjects, the experiments were scheduled to be at the same time session. The experimental session started about 8:00. There is no clock or watch in the laboratory. They had no knowledge about experimental duration.

Subjects were seated in a dimly lit, sound-attenuated, electrically shielded room. Before starting the experiment, the subjects completed a brief demographic questionnaire (age, handedness, hours of sleep, etc.), and ensured that the instructions were understood. First, the psychological self-report measures of sleepiness and fatigue were conducted. Subjective sleepiness was assessed by means of the Stanford Sleepiness Scale and the Karolinska sleepiness scale, and subjective fatigue was measured with the help of the Samn–Perelli checklist, Li's subjective fatigue scale and Borg's CR-10 scale [4,17–20]. Subsequently, the subjects were required to simply relax and try to think of nothing in particular, and recorded the EEG in the eyes-closed resting state for 5 min before starting the experimental session. They then performed the cognitive task either until 2 h elapsed or until volitional exhaustion occurred. Subjects were instructed to respond as quickly as possible, maintaining a high level of accuracy. Similar EEG recording was conducted immediately after the completion of the cognitive task. The same psychological rating was also carried out. The measurements were carried out at two epochs: pre-task, that was before task; post-task, that was immediately after task.

EEGs were recorded by a Neuroscan 32 channel system (Neuroscan, El Paso, TX, USA) with international 10–20 lead systems. Fp2, Fp1, F4, F3, A2, A1, C4, C3, P4, P3, Fz, Cz and Pz leads were used with Ag/AgCl electrodes. Recordings were referenced to linked-mastoids. Two additional bipolar pairs of electrodes were placed to record horizontal and vertical EOG. Skin impedance was below 5 kΩ on all electrodes. Physiological signals were filtered by band pass filter with bandwidth from 0.01 to 100 Hz. The signal was sampled at 500 Hz and digitized at 16 bit. Eye movement contamination was removed from EEG signal by the adaptive filter based on least mean square algorithm. Artifact rejection is done by visually inspecting the EEG.

2.3. Feature extraction based on complexity parameters

Two complexity parameters: approximate entropy (*ApEn*) and Kolmogorov complexity (*Kc*) are used to quantify the complexity of EEG under two mental fatigue states [21–25].

In the present study, after artifact detection and ocular correction, 1-min EEG data of each trial for each subject in the session of pre-task and post-task are selected to be analyzed. The EEG signal is then down re-sampled at 250 Hz before it is analyzed by using wavelet packet and nonlinear complexity methods. The first 10 s EEG data is chosen as basic data segment and steps by 1 s data. By shifting the data segment step-by-step for whole trial, 5100 data segments are obtained.

Wavelet packet analysis is performed to every EEG data segment [26,27]. Daubechies 10 is adopted as the mother wavelet. After eight-octave wavelet packet decomposition, the EEG components of the following five frequency bands are obtained: total (0.5–30 Hz), delta (0.5–3.5 Hz), theta (4–7 Hz), alpha (8–12 Hz), and beta (13–30 Hz). Then *ApEn* and *Kc* are calculated (Appendices A and B) for all EEG data segments in five frequency bands, respectively.

2.4. Reducing the dimensionality of feature vectors based on KPCA algorithm

KPCA is a technique of generalizing linear PCA into nonlinear case by using the kernel method [28,29]. As a nonlinear feature