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Estimating mental fatigue based on electroencephalogram and heart rate variability

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The effects of long term mental arithmetic task on psychology are investigated by subjective self-reporting measures and action performance test. Based on electroencephalogram (EEG) and heart rate variability (HRV), the impacts of prolonged cognitive activity on central nervous system and autonomic nervous system are observed and analyzed. Wavelet packet parameters of EEG and power spectral indices of HRV are combined to estimate the change of mental fatigue. Then wavelet packet parameters of EEG which change significantly are extracted as the features of brain activity in different mental fatigue state, support vector machine (SVM) algorithm is applied to differentiate two mental fatigue states. The experimental results show that long term mental arithmetic task induces the mental fatigue. The wavelet packet parameters of EEG and power spectral indices of HRV are strongly correlated with mental fatigue. The predominant activity of autonomic nervous system of subjects turns to the sympathetic activity from parasympathetic activity after the task. Moreover, the slow waves of EEG increase, the fast waves of EEG and the degree of disorder of brain decrease compared with the pre-task. The SVM algorithm can effectively differentiate two mental fatigue states, which achieves the maximum classification accuracy (91%). The SVM algorithm could be a promising tool for the evaluation of mental fatigue.

Fatigue, especially mental fatigue, is a common phenomenon in modern life, is a persistent occupational hazard for professional. Mental fatigue 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. Therefore, the evaluation of mental fatigue is important for the occupational risk protection, productivity, and occupational health.

Key words: mental fatigue; Electroencephalogram (EEG); heart rate variability (HRV); wavelet packet parameters; power spectral; support vector machine (SVM).

Introduction

Mental fatigue usually refers to the effects that people may experience after or during prolonged periods of cognitive activity [3]. In this study we define mental fatigue as a change in psychophysiological state due to sustained performance [6, 15]. This change in psychophysiological state has subjective and objective manifestations, which include an increased resistance against further effort, an increased propensity towards less analytic information processing, and changes in mood.

Mental fatigue is a very common phenomenon in the life, and is inevitable for office workers in general, which affects the individual's life quality on different aspects. When people become fatigued, they usually experience difficulties in maintaining task performance at an adequate level [4]. In industry, many incidents and accidents have been related to mental fatigue as the result of sustained performance. 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 detect mental fatigue changes. A large number of studies have found that many critical laws using behavioural indices or subjective measures. However, these measures have some limitations, for instance, they cannot provide moment-to-moment fluctuations of mental fatigue. Moreover the results may be affected by the subjects' cognitive ability, mood and anxiety levels [12, 20]. A recent tendency in ergonomic research is to choose physiological indices 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. Several scholars reported that performing monotonous tasks were related to the increase of the 0.1 Hz component in the heart rate variability (HRV) [21-22, 28]. Although numerous physiological indicators are available to describe an individual's mental fatigue state, the EEG signal has been shown to be the most promising, predictive and reliable, because it is directly related to neuronal activity in the cerebral cortex [14, 18-19]. The EEG is widely regarded as the physiological ‘gold standard’ for the assessment of mental fatigue. There were several EEG studies related to mental fatigue in the past. Some studies reported EEG spectral changes as alertness declines. For example, the proportion of low frequency EEG waves, such as theta and alpha rhythms, may increase while higher frequency waves, such as beta rhythms may decrease [8, 17, 31, 35]. Other studies explored the links between fatigue and changes in event-related potential components. Mental fatigue was found to produce a decrease in P300 amplitude while latency increases [3, 25].

However, mental fatigue is a complex phenomenon, which is influenced by the environment, the state of health, vitality, and the capability of recovery. Single physiological parameter cannot evaluate mental fatigue well. It would preferably need to consider more physiological measures. Thus, several techniques need to be combined to estimate the state of mental fatigue.

In this paper, subjective self-reporting measures and action performance test are utilized to verify that long term mental arithmetic task would induce the mental fatigue to the subjects. Moreover the impacts of prolonged cognitive activity on central nervous system and autonomic nervous system are further observed and analyzed by means of electroencephalogram (EEG) and heart rate variability (HRV). Then wavelet packet features of EEG which change significantly are extracted for every EEG data segments of pre-task and post-task, and these features are then considered as inputs of support vector machine (SVM). Finally two mental fatigue states are differentiated by SVM algorithm. Compared with previous studies, the presented comprehensive methods would make the mental fatigue estimation much reliable and accuracy since many psychological and physiological parameters are considered.

Materials and methods

Subjects

Eighteen male right-dominated graduate students, between 21 and 26 years old (M = 23.1 years, SD = 1.4), participated in this study. However, two were excluded because they were not serious and struggling in the experiment which led to extremely slow response times. 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 patterns. They all accustomed to operating a computer keyboard and a mouse. Informed consent had been obtained from all subjects prior to the study.

Experimental task

Participants were comfortably seated facing a videomonitor at about 50 cm far. The experimental task was the simple arithmetic calculation, which was consisted of four randomly generated single digits, two operators (+, –), and three comparison symbols (<, =, >). They were displayed on a computer monitor continuously until the subject responded (Figure 1). The participants solved the problems firstly, and then decide whether the result was less than, equal to, or greater than the target sum provided. They indicated their decision by pressing the appropriate key labeled <, =, and >, respectively. Participants were instructed to answer as quickly as possible. They performed the task until either they quitted from exhaustion or two hours elapsed. The response time and the error trial, if any, were recorded.

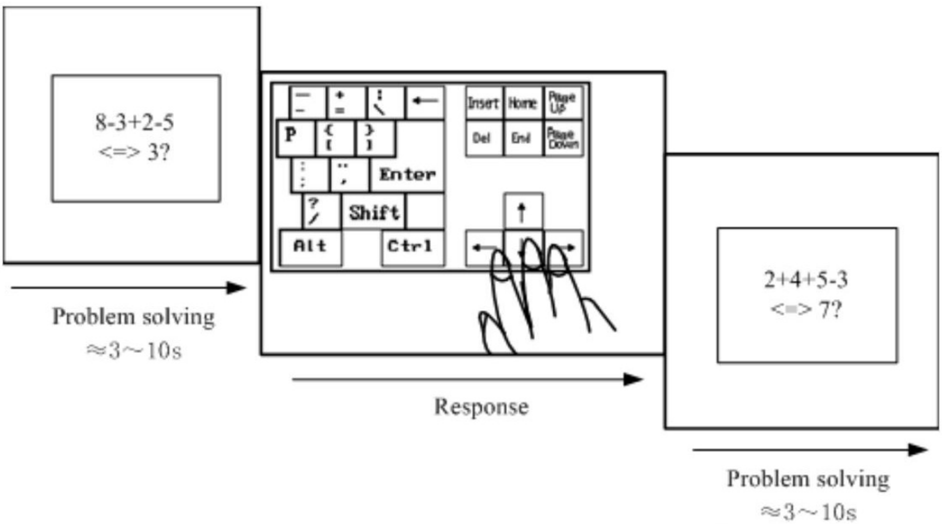

Figure 1. Schematic diagram of events in the mental arithmetic task.

Data acquisition

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. Electrocardiogram (ECG) was measured with three disposable electrodes. Two electrodes were attached on the left and right sides of frontal lower ribs. The grounding electrode was placed on the sternum. 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 by adaptive filtering methods.

Experiment design

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 and lasted for 3.5 to 4 hours. No any clock and 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 subjective self-report measures of fatigue were conducted. Subsequently, the subjects were required to simply relax and try to think of nothing in particular, and recorded the EEG and ECG in the eyes-closed resting state for five minutes before starting the experimental session. They then performed the mental arithmetic task either until two hours elapsed or until volitional exhaustion occurred. Subjects were instructed to respond as quickly as possible, maintaining a high level of accuracy. Similar EEG and ECG recordings were conducted immediately after the completion of the mental arithmetic task. The same subjective rating of fatigue was also carried out. The measurements were carried out at two epochs: pre-task, that is before task; post-task, that is immediately after task.

Data analysis

To investigate the effects of time on task and probe into the relationship between mental fatigue state and psychophysiological parameters, the power spectral of HRV, relative wavelet packet energy and wavelet packet entropy of EEG, and subjective self-report measures were used. The difference between psychophysiological index pre- and post task was analyzed with a paired-samples T test. All the analyses were conducted with statistical software SPSS.

Results

Subjective and performance evaluation of fatigue

It was hypothesized that, compared with the pre-task, the efficiency of performing the mental arithmetic task under the post-task and the subjective scores (sleepiness and experienced fatigue) were negatively affected by the mental demands of the preceding hours. In order to validate this hypothesis, several subjective scales and performance measures were used before and after the task.

Subjective sleepiness was assessed by means of the Stanford Sleepiness Scale (SSS) [13] and the Karolinska Sleepiness Scale (KSS) [1], and subjective fatigue was rated on the Samn-Perelli checklist (SPC) [30], Li's subjective fatigue scale (SFS) [21] and Borg's CR-10 scale (CR-10) [5]. The results of comparison of several subjective scores between two sessions were shown in Figure 2.

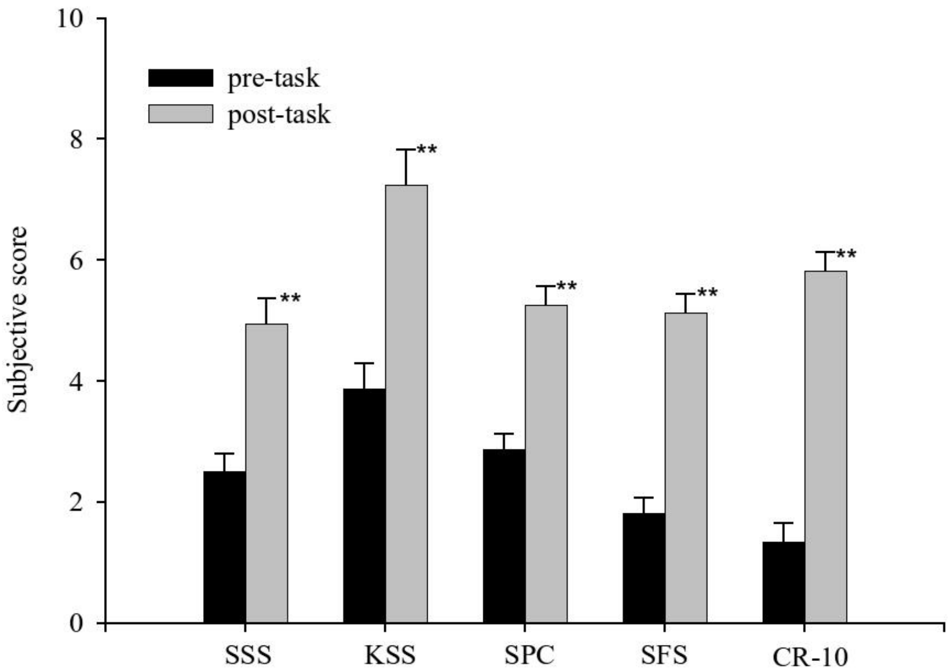

Figure 2. Comparison of several subjective scores on mental fatigue between two sessions. Pre-task: before task, post-task: immediately after task. $^{**}P < 0.005$, statistical significance of difference between two sessions.

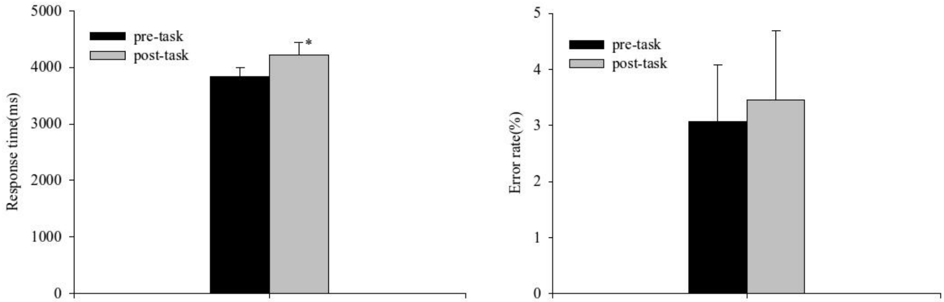

Figure 3. Comparison of mean response time and error rate between two sessions. Pre-task: before task, post-task: immediately after task. *$P < 0.05$, statistical significance of difference between two sessions.

The self-report questionnaires revealed subjects were not fatigue and sleepy before task and moderately to extremely fatigue and sleepy after task. Compared with the pre-task, the subjective scores increased significantly ($P < 0.005$) after the completion of the task.

When working for a considerable time on a particular task, there would be no doubt to result in mental fatigue which in turn affected performance. Thus, to examine the effects of mental fatigue on the performance of subjects, mean correct response times (RTs) and error rate (ER) of ten-minute arithmetic task for each trial at the beginning of the pre-task and at the end of post-task were calculated. The results of comparison of mean correct RTs and ER between two sessions were shown in Figure 3.

It could be seen that mean correct RTs increases significantly while ER did not change significantly in the post-task. The results suggested that the efficiency of perform for subjects declined after long term cognitive task.

Based on the subjective and performance evaluation, it could be judged that long term cognitive task induced an increase in fatigue and sleepiness to subjects.

Power spectral of HRV

Power spectrum analysis of HRV was a sensitive and non-invasive technique to quantify the autonomic control over the cardiac cycle [23]. Using spectral analysis, the influences of the sympathetic and parasympathetic divisions of the autonomic nervous system on

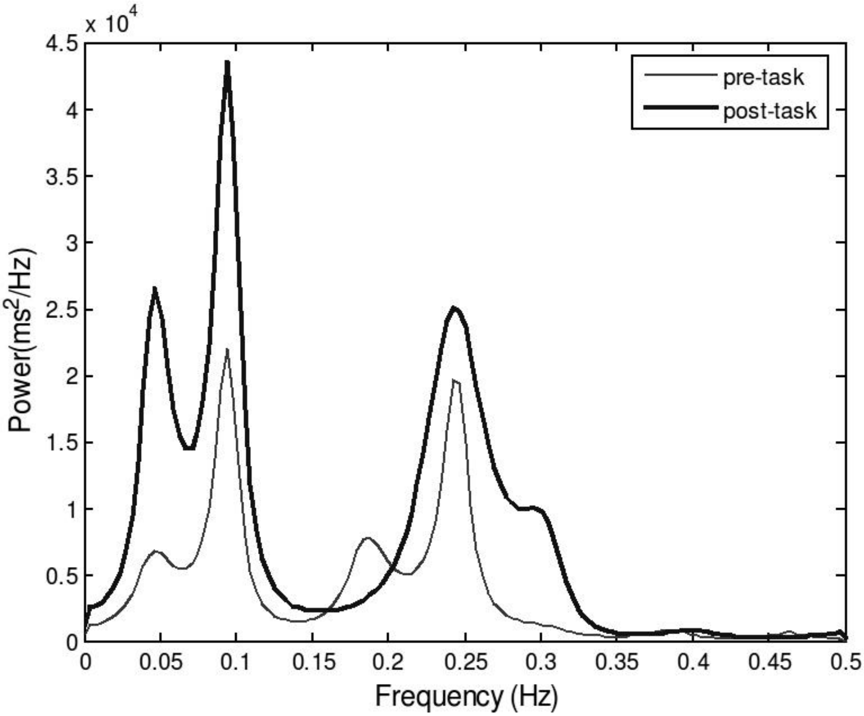

Figure 4. Comparison of power spectral of HRV between two sessions of pre-task and post-task.

modulation of the cardiac cycle may be quantified in spectral bands. The technique of frequency domain analysis usually used high-frequency (HF: 0.15-0.40 Hz) power as an index of parasympathetic activity and the low-frequency (LF: 0.04-0.15 Hz) power as an index of sympathetic and parasympathetic activity [26]. Thus, The LF/HF ratio was considered to mirror sympathovagal balance [24] or to reflect the sympathetic modulations [2, 29].

The detection of R waves was done by the algorithm based on wavelet transforms. Then 5-min raw RR interval sequence was interpolated at 1-second intervals by linear interpolation. From the interpolated RR tachogram, the power spectrum of HRV was estimated from 256 R-R intervals of the heart beat by using an autoregressive (AR) model (order 16). When RR spectrums were investigated, it was observed that a considerable amount of energy was in the very LF range (< 0.03 Hz). Very LF oscillations were much less defined but suggested to be related with thermoregulation. Therefore, to prevent these oscillations from masking other frequency ranges (< 0.03 Hz), they were filtered from the tachograms by using wavelet filter before modeling.

For spectral analysis, the total power (TP: 0-0.4 Hz), LF power, HF power and LF/HF ratio were calculated. Spectrum components were expressed both in absolute unit (AU, ms^2) and normalized unit (NU). The normalized value of equation of the LF power was represented as

$$\text{LF power (NU)} = \frac{\text{LF power}}{\text{TP power} - \text{Very LF power}}$$

Figure 4 presented the comparison of power spectral of HRV between two sessions of pre-task and post-task. It was obvious that both LF power and TP power increased after task.

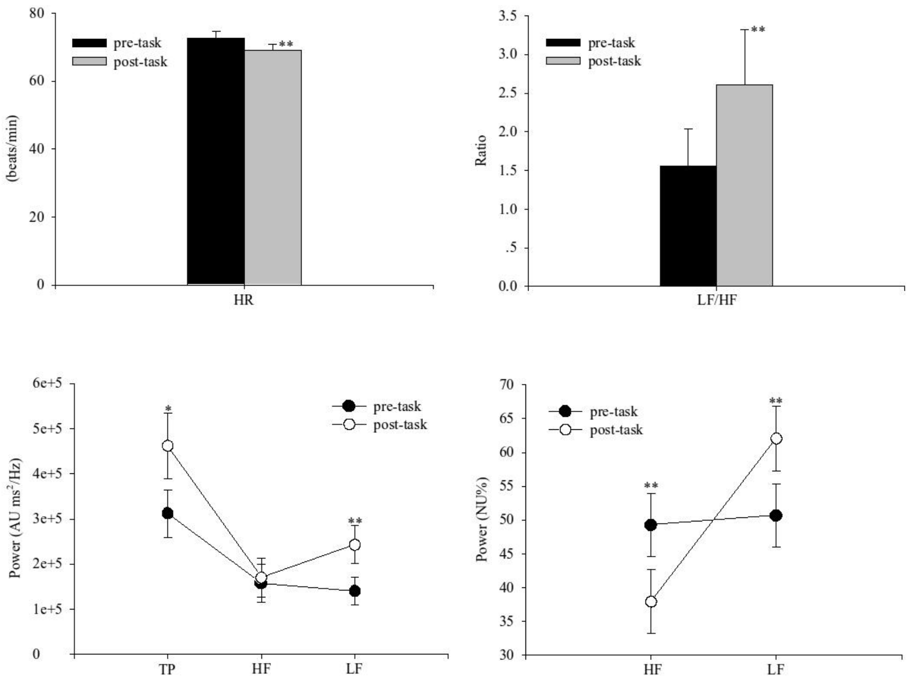

Figure 5. Comparison of heart rate (HR), TP power, HF power (AU and NU), LF power (AU and NU) and LF/HF ratio of HRV between two sessions. Pre-task: before task, post-task: immediately after task. $^*P < 0.05$, $^{**}P < 0.005$, statistical significance of difference between two sessions.

Mean values of heart rate (HR), TP power, HF power (AU and NU), LF power (AU and NU) and LF/HF ratio of HRV between the pre-task and post-task periods were shown in Figure 5.

Compared with the pre-task, mean HR and HF power (NU) decrease ($P < 0.005$), while TP power, LF power (AU and NU) and LF/HF ratio increased ($P < 0.05$) after the task. However, HF power (AU) did not change significantly.

Relative wavelet packet energy and wavelet packet entropy of EEG

In addition to the HRV analysis, we performed a wavelet packet analysis to the EEG data. Daubechies 10 (db10) was adopted as the mother wavelet. After eight-octave wavelet packet decomposition ($j = 1, \ldots, 8$), the EEG components of the following four frequency bands were obtained: δ(0.5-3.5 Hz), θ(4-7 Hz), α(8-12 Hz), β(13-30 Hz). The relative wavelet packet energy of β frequency band, denoted by $RWPE_\beta$ was defined as

$$RWPE_\beta = \frac{\text{wavelet packet energy of } \beta}{\text{wavelet packet energy of } (0.5-30)\,\text{Hz}}$$

We defined the wavelet packet entropy as

$$S_{WPE} = -\sum_j p_j \cdot \ln(p_j),$$

the distribution $\{p_j\}$ could be considered as the relative wavelet packet energy of four frequency bands.

Using these methods, relative wavelet packet energy indices of four frequency bands were obtained. The ratio indices β/α, θ/α, $(\alpha + \theta)/\beta$ and the wavelet packet entropy were calculated. These ratio indices of EEG were reported to relate with sleepiness [16].

After artifact detection and ocular correction, one-minute EEG data of each trial for each subject in the session of pre-task and post-task were selected to be analyzed. The first 10 seconds EEG data was chosen as basic data segment and stepped by one second data. By shifting the data segment step-by-step for whole trial, 1632 data segments were obtained. Then relative wavelet packet energy indices in four frequency bands, wavelet packet entropy, the ratio indices β/α, θ/α, and $(\alpha + \theta)/\beta$ for all EEG data segments were calculated. To eliminate the influences of parameter's fluctuation, the mean value within one minute was calculated to be statistically analyzed.

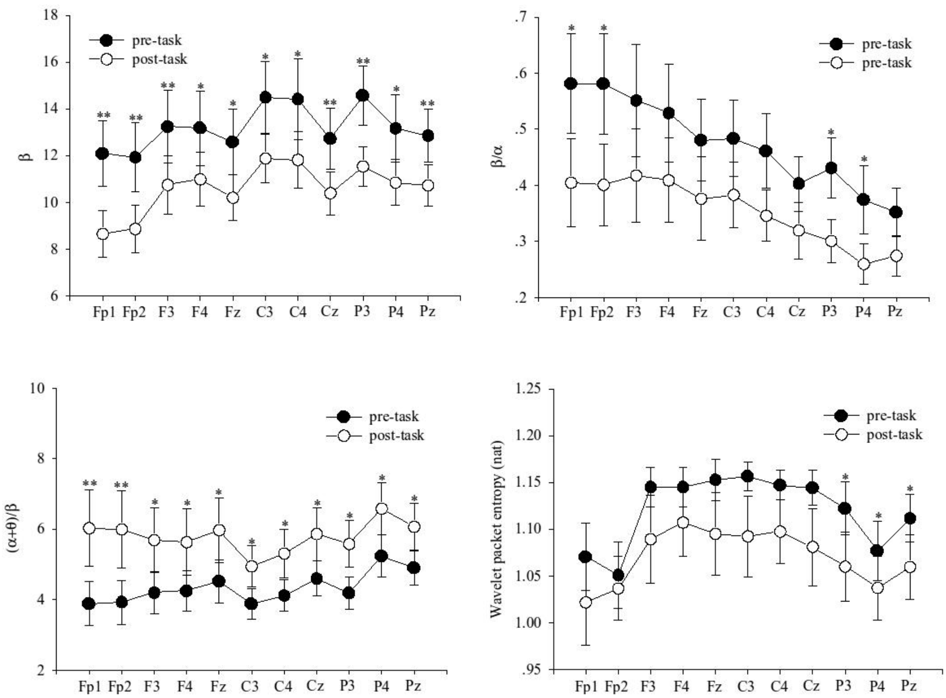

Figure 6. Comparison of relative wavelet packet energy in β frequency band, β/α, (α + θ)/β and wavelet packet entropy between two sessions. Pre-task: before task, post-task: immediately after task. *$P < 0.05$, **$P < 0.005$, statistical significance of difference between two sessions.

The results of comparison of relative wavelet packet energy in β frequency band, β/α, (α + θ)/β and wavelet packet entropy between two sessions were shown in Figure 6.

Compared with the pre-task, mean value of relative wavelet packet energy in β frequency band on all electrodes significantly decreased ($P < 0.05$), mean value of β/α on prefrontal and parietal electrodes significantly decreased ($P < 0.05$), mean value of wavelet packet entropy on parietal electrodes significantly decreased ($P < 0.05$), while mean value of (α + θ)/β significantly increased ($P < 0.05$) after the completion of the task. However, mean value of relative wavelet packet energy in the other three frequency bands and θ/α on all electrodes did not change significantly.

The classification results of SVM

The experimental results of subjective measure and power spectrum analysis of HRV verified that the level of both subjective sleepiness and fatigue increased significantly after long term mental arithmetic task. The subjects were not fatigue and sleepy before task, corresponded to a normal arousal state, and moderately to extremely fatigue and sleepy after task. In order to differentiate the normal state from fatigue state, 29-dimension wavelet packet features which changed significantly in statistical analysis were firstly extracted for every EEG data segments of pre-task and post-task, and these features were then considered as inputs of SVM. Finally the mental fatigue state was decided by SVM algorithm.

Cross-validation was a standard test commonly used to test the ability of the classification system using various combinations of the testing and training data sets. A 5-fold cross-validation test was applied. We randomly selected 80% of recording data sets for training the classifier, and the 20% remained for testing, the classification accuracy of each task was calculated with different random selections of training and testing set.

For SVM classifier, the range of the parameter σ?was from 0.5 to 3, and the classification accuracy was calculated for each parameter σ. The classification result of SVM was shown in Figure 7.

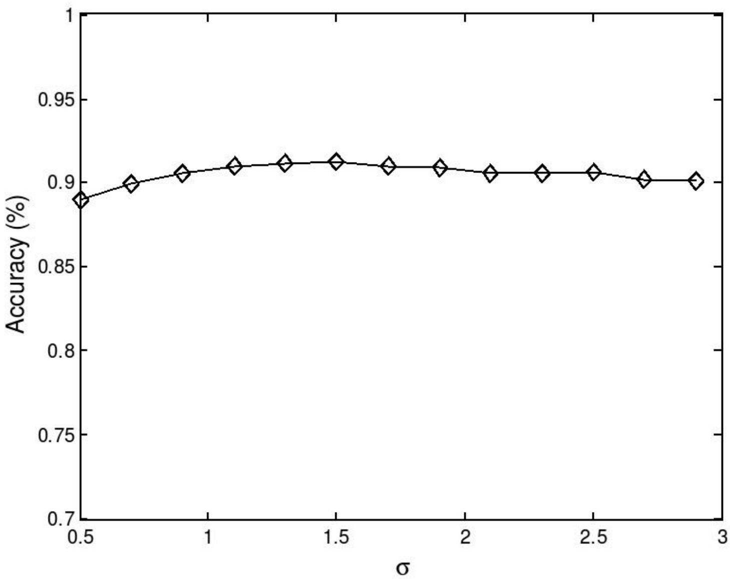

Figure 7. Classification result of SVM versus σ.

From Figure 7, it could be seen that the SVM algorithm could distinguish two mental fatigue states effectively which achieved the maximal classification accuracy (91%) while the kernel parameter σ?equals to 1.5.

In Table 1, we compared the performance of SVM to that of linear discriminant analysis based on Mahalanobis distance (MDBC). Three measures, accuracy (Ac), specificity (Sp) and sensitivity (Se) were used to assess the performance of two classifiers [27]. Accuracy indicated overall detection accuracy; specificity was defined as the ability of the classifier to recognize a fatigue state whereas sensitivity would indicate the classifier's ability not to generate a false detection (normal state).

Table 1. The comparison of the best performance of MDBC and SVM.

Techniques	Ac	Sp	Se
SVM	0.91	0.91	0.92
MDBC	0.80	0.80	0.79

MDBC is the linear discriminant analysis based on Mahalanobis distance; The kernel function of SVM is RBF function.

According to the records, the SVM algorithm was shown to classify mental fatigue with higher classification accuracy (91%), which exceeded that of MDBC to a great extent. This demonstrated that SVM algorithm was a promising classifier for mental fatigue.

Discussion

As already mentioned in the introduction, there is a strong link between mental fatigue and the autonomic nervous activity: performing monotonous tasks is related to the increase of the LF component in HRV. LF component of the power spectrum of the HRV reflects both sympathetic and parasympathetic activities [11]. Parasympathetic outflow is estimated as the HF component of the power spectrum of HRV, and balance between sympathetic and parasympathetic outflow as the LF/HF ratio. In the present study, there is significant increase in the TP, LF power (AU and NU) and LF/HF ratio, and a significant decrease in the HF power (NU) after the task when compared with the pre-task period, indicating a shift of sympathovagal balance toward a sympathetic predominance and a reduced vagal tone in the fatigue state. This is consistent with the analysis of theory. Heart is controlled by both sympathetic and parasympathetic activities. When subject is at ease, it is modulated by sympathyovagal balance; on the contrary, the sympathetic activity is predominant when subject is fatigued, excited and nervous. Therefore, the predominant activity of autonomic nervous system of subjects turns to the sympathetic activity from parasympathetic activity after the task. However, heart rate show the opposite course as is expected. Continuously tasking time does not lead heart rate to increase. This is in line with the course of the LF component. Lower heart rate causes more variations in heart rate and this is reflected in an increase of the LF component.

The changes of beta rhythms are related with mental fatigue closely. The beta rhythms are generally considered as fast waves, which are associated with increased alertness, arousal and excitement. In this study, relative wavelet packet energy of β rhythms shows a significant change after long term sustained mental arithmetic task, and it is consistent with previous studies in sleep deprivation [8]. The results indicate that the subjects' alertness level declines greatly, and the excitement level of brain decreases after the completion of the task.

Among the ratio indices, index β/α, and index $(\alpha + \theta)/\beta$ are statistically significant in this experiment. It has been recognized that theta waves are associated with a variety of psychological states including hypnagogic imagery, low levels of alertness during drowsiness and sleep and as such have been associated with decreased information processing [17], alpha waves occur during relaxed conditions, at decreased attention levels and in a drowsy but wakeful state, and beta waves is related to alertness level, and as the activity of beta band increases, performance of a vigilance task also increases [31]. In our experiment, the mean value of β/α on prefrontal and parietal electrodes decreases significantly, while mean value of $(\alpha + \theta)/\beta$ increases significantly on all electrodes after the task. These ratio indices can reflect the changes of theta, alpha, beta rhythms and the change of mental fatigue further. It is suggested that the alertness level of subjects decreases after task, which induces slow waves of EEG increase and the fast waves decrease. The ratio index β/α and $(\alpha + \theta)/\beta$ are sensitive to the change of mental fatigue.

Wavelet packet entropy, as a measure of the degree of order/disorder of the signal frequency, can provide useful information about the underlying dynamical process associated with the signal. When subject feels fatigue, the brain will be restrained, so the degree of disorder of brain decrease, this will result in the decrease of wavelet packet entropy of EEG finally. Wavelet packet entropy of EEG significantly decreases after the task. The experimental results agree with the theoretical analysis.

The performance of SVM classifier is nonsensitive to the sample size and the dimensionality. It eliminates many of the problems experienced with NN such as local minima and over fitting [37]. In addition, its ability to produce stable and reproducible results makes it a good candidate for solving many classification problems. So SVM algorithm shows better performance than traditional linear discriminant analysis in this paper.

Conclusion

Long term mental arithmetic task has significant effect on psychology, behaviour and physiology of subjects, which induces the changes of subjective sleepiness and mental fatigue, performance, autonomic nervous function and central nervous system. In this paper we focus on the use of physiological measures to measure mental fatigue. The indices based on central nervous system (EEG) and those based on autonomic nervous function such as HRV are combined to monitor the change of mental fatigue. There is a close relationship between changes in fatigue and the physiological parameters. These physiological parameters may serve as indicators of the level of mental fatigue. For mental fatigue classification, experimental results suggest that SVM algorithm might be a useful tool for the estimation of mental fatigue.

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