Mental Fatigue Estimation Using EEG in a Vigilance Task and Resting States

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***Abstract*—Mental fatigue induced by long time mental work can cause deterioration in task performance and increase the risk of accidents. Recently, electroencephalogram (EEG)-based monitoring of mental fatigue has received increasing attention in the field of brain-computer interfaces (BCI). This study aims to employ EEG signals to measure the mental fatigue level by estimating reaction time (RT) in a psychomotor vigilance task (PVT). In a 36-hour sleep deprivation experiment, EEG data from 18 subjects were recorded every four hours in nine blocks, each consisting of three tasks: a 6-minute PVT task and two 3-minute resting states (eyes closed and eyes open). The mean RT in the PVT task showed a generally increasing trend during the 36-hour awake period, reflecting the increase of fatigue over time. For each task, multiple EEG features were extracted and selected to better estimate RT using a multiple linear regression (MLR) method. The correlation between predicted RT and actual RT was evaluated using a leave-one-subject-out (LOSO) validation strategy. After parameter optimization, EEG data from the PVT task obtained a mean correlation coefficient of 0.81±0.16 across all subjects. Resting-state EEG data showed lower correlations (eyes-closed: 0.65±0.20, eyes-open: 0.50±0.30) partially due to the involvement of shorter data lengths. These results demonstrate the feasibility and robustness of the EEG-based fatigue monitoring method, which could be potential for applications in operational environments.**

I. Introduction

Mental fatigue is considered to be associated with a disinclination for any effort, reduced efficiency and alertness, and impaired mental performance [1]. A fatigue state can cause severe performance deterioration, which may lead to increased errors and accidents. It is therefore important to find reliable indicators of fatigue and develop countermeasures. The technology for monitoring fatigue has greatly improved over the past several decades. Many different approaches such as electroencephalogram (EEG), eye movements assessed by electroocculogram (EOG) or eye tracking, heart rate, computer vision that detects body or face states, psychomotor tests, and subjective questionnaires, have been developed to measure fatigue. Among these methods, EEG might be one of the most valid and promising indices of fatigue because it provides a direct measurement of brain states.

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Sleep deprivation is a stable way to induce fatigue and sleepiness that increase during prolonged wakefulness, which can lead to distinct changes in EEG. EEG during resting awake periods with eyes closed shows a positive correlation of theta power (4-8Hz) and a negative correlation of alpha power (8-12Hz) to the subjective sleepiness in sleep deprivation [2]. As fatigue increases, power spectrum density (PSD) in alpha band increases when eyes open but decreases when eyes closed. The ratio between alpha power in eyes-open and eyes-closed conditions, which is called Alpha Attenuation, can be used as a fatigue indicator [3]. In EEG-based fatigue detection, PSDs of different frequency bands and their ratios have been widely used [4], [5]. In addition to PSD features, event-related potentials (ERPs) in the time domain provide another type of features for detecting fatigue. Amplitudes of the visual ERPs are inversely correlated and the latencies are positively correlated with hours of sleep deprivation [6].

In EEG-based fatigue estimation, classification and regression are the two basic methods. The classification method generally divides brain states into two or more levels of alert and fatigue. Leonard et al. designed 3-hour continuous math problem solving tasks to induce fatigue and obtained 97% accuracy in the binary classification of alert and fatigue states [7]. Shen et al. classified EEG into five mental-fatigue levels and obtained 91% accuracy in a 25-hour sleep deprivation experiment [8]. The regression method aims to predict a continuous fatigue level by modeling the relationship between EEG and fatigue. Lin et al. used support vector regression (SVR) to predict reaction time (RT) with EEG in a simulated driving experiment and obtained root mean square error (RMSE) minimized to 124ms [9]. To our knowledge, the regression method for fatigue estimation in sleep deprivation has not been reported before. This study aims to develop a robust regression method to detect fatigue with EEG features from resting and vigilance tasks during sleep deprivation.

In this study, EEG data from alert to fatigue in a psychomotor vigilance task (PVT) and two resting states (eyes closed and eyes open) were collected during a 36-hour sleep deprivation. A multiple linear regression (MLR) method was used to model the relationship between EEG and RT in the PVT task. To avoid overfitting, a leave-one-subject-out (LOSO) cross validation was used to evaluate the correlation between the predicted RT and the actual RT, which could reflect the performance of fatigue estimation.

II. Methods

A. Participants

Eighteen healthy subjects (13 males, mean age: 21 years) participated in the experiment. Each subject was asked to read and sign an informed consent form before the experiment.

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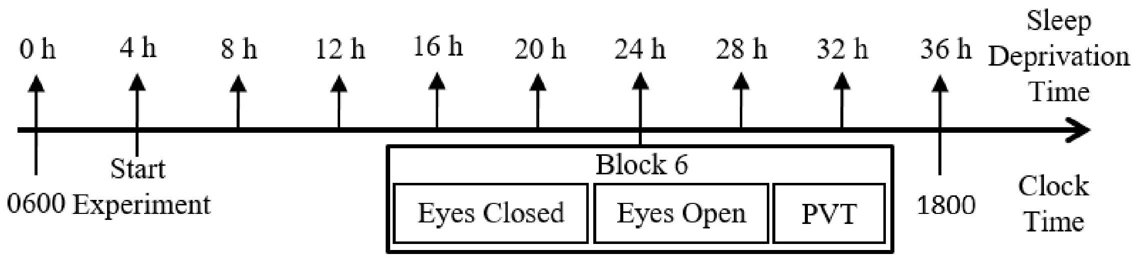

Figure 1. Schematic diagram of the 36-hour sleep deprivation experiment.

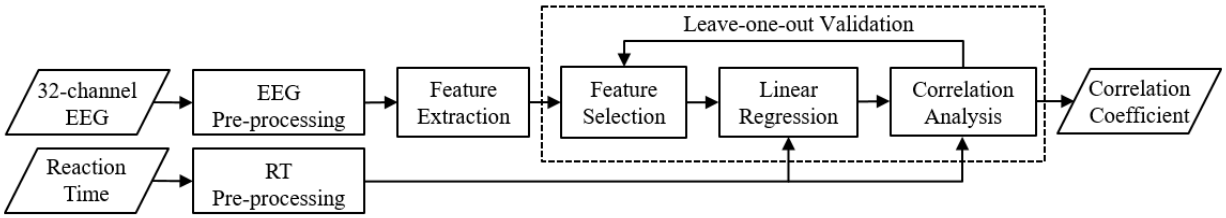

Figure 2. Flowchart of data analysis with EEG and RT.

They were prohibited from alcohol, smoking, and coffee within 48 hours before the experiment.

B. Experimental Tasks

This study performed a 36-hour sleep deprivation experiment. As shown in Figure 1, the subjects got up from 6 a.m. in the morning on Day 1 and started the experiment at 10 o'clock. Nine blocks of EEG were recorded every four hours till the experiment ended at 18 o'clock in the afternoon on Day 2. Each block contained three tasks: a 3-minute eyes-closed resting state, a 3-minute eyes-open resting state, and a 6-minute PVT task. Subjects were seated in a comfortable chair in a normally lit room at a viewing distance of approximately 60 cm from a computer monitor. The subjects were instructed to fixate at a fixation cross on the screen during the eyes-open resting condition. In the PVT task, a fixation cross appeared on the screen at the beginning and then switched to a millisecond counter. The subjects were asked to press the space bar as soon as possible using the right index finger, which stopped the counter and displayed the RT. Interval between trials varied between 2 and 10 seconds. The program was developed under MATLAB (MathWorks, Inc.) using the Psychophysics Toolbox Version 3 [10].

C. Data Acquisition and Analysis

32-channel EEG data including two EOG channels (VEOG and HEOG) were recorded using a SymAmp2 system (Neuroscan, Inc.) according to the international 10–20 system. The sampling rate was 1000Hz and the electrode impedance was kept below 10 kΩ.

Figure 2 illustrates the flowchart of data analysis with EEG and RT. The main procedures include data preprocessing, feature extraction, feature selection, linear regression, and correlation analysis. An LOSO cross validation applies to feature selection, linear regression, and correlation analysis.

D. Data Pre-processing

The raw EEG signals were band-pass filtered by a finite impulse response (FIR) filter in the range of 1-45Hz. In the PVT task, 1.5-second data epochs time locked to stimulus ([-500ms 1000ms]) and response ([-1000ms 500ms]) were extracted separately for ERP analysis. For each subject, mean RT of each block was calculated by averaging RTs for all trials in the block.

E. Feature Extraction and Selection

PSDs of EEG were calculated by applying a Welch's periodogram method to 1-second data segments with 50% overlap from continuous data. PSD features were defined as the mean band power (BP) corresponding to four frequency bands (delta: 1-4Hz, theta: 5-7Hz, alpha: 8-12Hz, and beta: 13-30Hz) and the accumulated power (AP) in the range of 1-30Hz. Two other PSD-based features, frequency variability (FV) and center of gravity frequency (CGF) [11], were extracted. FV is defined as:

$$\mathrm{FV} = \frac{\sum_i P(f_i)\times f_i^2 - \frac{\left(\sum_i P(f_i)\times f_i\right)^2}{\sum_i P(f_i)}}{\sum_i P(f_i)} \tag{1}$$

and CGF is defined as:

$$\mathrm{CGF} = \frac{\sum_i P(f_i)\times f_i}{\sum_i P(f_i)} \tag{2}$$

where f_i is frequency and $P(f_i)$ is the estimated PSD (i = 1, 2… 30). Considering $P(f_i)$ as the probability distribution of frequency, FV is the variance of the frequency in the selected frequency band [11]. In addition to PSD features, ERP features in the PVT data were extracted by averaging all trials in each block. For stimulus-locked ERP (sERP), three time windows (tw1: 0-250ms, tw2: 250-600ms, tw3: 600-1000ms) [6] were separated to calculate maximum and minimum peak amplitudes and corresponding latencies. For response-locked ERP (rERP), two time windows (tw1: -1000-0ms, tw2: 0-500ms) were used for extracting amplitude and latency features.

According to feature extraction methods described above, there were 13 basic features (BP, FV, CGF features for 4

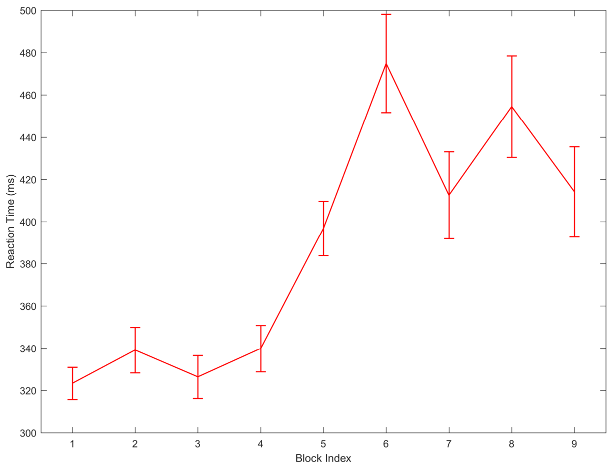

Figure 3. Mean RTs of all subjects in 9 blocks throughout 36-hour sleep deprivation. The error bars indicate standard errors.

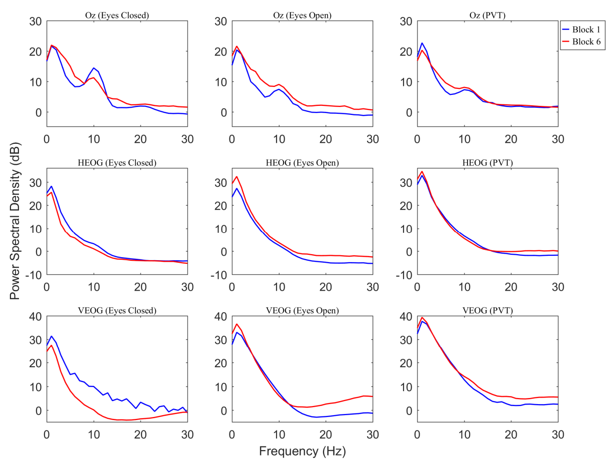

Figure 4. PSDs at channels Oz, HEOG, and VEOG in block 1 and block 6 under three conditions.

frequency bands and an AP feature) for the eyes-closed and eyes-open conditions, and 33 basic features (including 20 ERP features) for the PVT condition. New ratio features were constructed using all combinations of feature pairs. For the resting conditions, there were 13 basic features and 78 ratio features, leading to a total of 2912 (91×32) features for 32 channels. 33 basic features and 528 ratio features for PVT resulted in 17952 (561×32) features. In feature selection with a large number of features, greedy search strategies [12] can be used to reduce computational cost and overfitting. This study used forward selection method to select a feature subset towards the highest correlation coefficient between the predicted RT and the actual RT. Before forward selection, all features were ranked in a descending order according to the correlation coefficients between single feature and RT.

F. Linear Regression and Correlation Analysis

In this study, the relationship between EEG features and RT was modelled with a multiple linear regression algorithm using least squares. The regression model is defined as:

$$y = \sum_{i=1}^{n} w_i x_i + w_0 \tag{3}$$

where x_i is the input of EEG features, n is the number of features, w_i is regression coefficient, w_0 is intercept, and y is the output of RT. After the regression analysis, Pearson's correlation coefficient between the predicted RT and the actual RT was calculated as performance metrics of fatigue estimation.

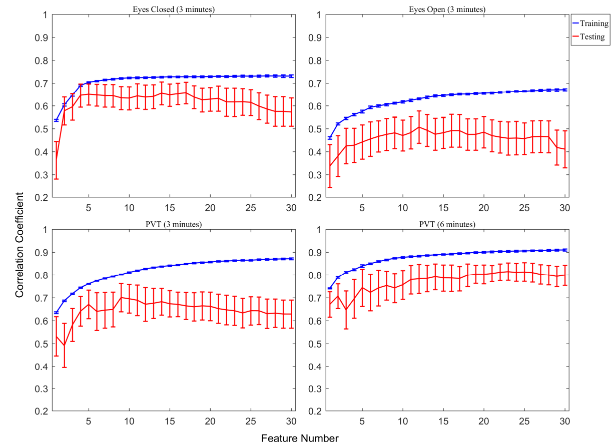

Figure 5. Mean correlation coefficients of training and testing sets with different feature numbers. A 3-minute PVT condition was added for comparison. The error bars represent standard errors across subjects.

G. Validation

To reduce overfitting in feature selection and model training, this study used LOSO cross validation to estimate the highest correlation between the predicted RT and the actual RT. Data for each of the 18 subjects were used as a testing set, and data for the remaining 17 subjects (training set) were used for feature selection and training of the regression model. After repeating 18 times where each subject was chosen as a testing set, the mean correlation coefficient of the testing sets was calculated as the final performance estimation. The search for the best feature subset was also performed in LOSO cross validation on the training set.

III. Results

A. RT

Figure 3 shows the mean RTs of all subjects during the experiment. In general, the mean RT increased from the minimum of 323±32 ms at block 1, and reached the maximum of 474±98 ms at block 6 (6 a.m. in the morning of Day 2). The fluctuation of RT on the second day can be explained by a circadian modulation superimposed on a global trend of increasing fatigue. One-way analysis of variance (ANOVA) indicated significant difference of RT across all blocks ($F(8,161)=11.43$, $p<0.001$). Post-hoc paired t-tests between different blocks showed that the difference of RTs between any one of the former four blocks and any one of the latter five blocks was significant ($p<0.05$).

B. PSDs

Figure 4 shows PSDs of EEG and EOG in block 1 and block 6. As the awake time increased, the alpha band activities at Oz decreased in the eyes-closed EEG, but increased in the eyes-open EEG. In contrast, EEG in the other frequency bands showed increased power in all conditions. These results are in line with previous studies [2], [3]. For EOG, almost all bands decreased in the eyes-closed condition while the delta and beta bands increased in the eyes-open and PVT conditions.

TABLE I. FEATURES SELECTED >10 TIMES IN LOSO CROSS VALIDATION FOR PVT DATA

Number of Times	Channel	Feature	Corr Coef
17	VEOG	CGF(δ)	-0.74
16	HEOG	FV(β)/BP(θ)	0.59
16	CPz	sERP_Max_L1/BP(β)	-0.33
15	FCz	sERP_Max_L3/BP(α)	0.37
12	P8	sERP_Max_A2/FV(δ)	0.48
12	FP1	rERP_Min_A1/FV(δ)	0.59
12	CPz	sERP_Max_L1/BP(θ)	-0.32
12	VEOG	BP(β)/BP(α)	0.46
11	F8	BP(α)/FV(δ)	0.55
11	P3	sERP_Max_L1/BP(θ)	-0.26

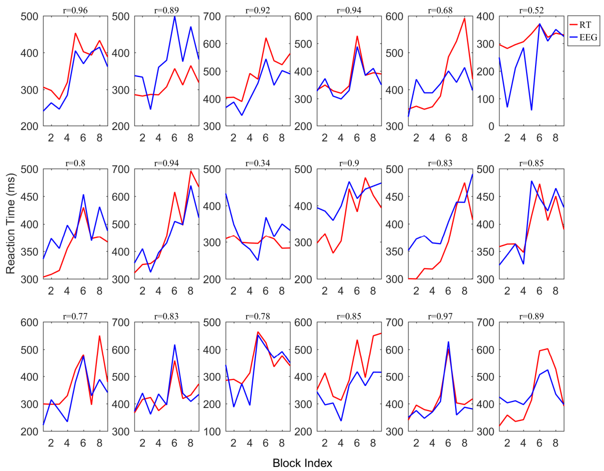

Figure 6. Predicted and actual RTs for all subjects using the best model from PVT data.

C. Correlation

Figure 5 shows mean correlation coefficients between predicted RT and actual RT with different feature numbers for all three conditions. There was clear performance decrease from training to testing in LOSO validation, suggesting individual difference. The training performance increases as the feature number increases. However, the testing performance reaches to the highest and decreases afterwards. To ensure generalizability, this study used the same number of features for all subjects. Data in the PVT condition showed the maximum correlation coefficient of 0.81±0.16 (range: 0.34-0.97) with 23 features. TABLE 1 lists the features selected in the 23-feature subset more than 10 times in the LOSO cross validation. Interestingly, most of the features were ratio features constructed by basic PSD and ERP features from EEG and EOG channels. Single features show correlation values up to 0.74. Figure 6 displays the predicted and actual RTs for all subjects using the best 23-feature models in the LOSO cross validation. Data of 6 subjects obtained correlation coefficients above 0.9. As shown in Figure 5, data from the two resting conditions show lower maximum correlation coefficients (eyes-closed: 0.65±0.20, eyes-open: 0.50±0.30) with a subset of 5 and 12 features. Since the PVT task included more data, to make a more reasonable comparison between the three conditions, a 3-minute PVT condition was added and obtained a maximum correlation coefficient of 0.70±0.26 with a subset of 9 features. This finding suggests that data from all of the designed PVT and resting conditions can be used to estimate mental fatigue. Besides, the increase of data length in one condition could be an efficient way to improve the prediction performance.

IV. CONCLUSION AND DISCUSSIONS

This study developed a regression method to estimate mental fatigue in 36-hour sleep deprivation using EEG. With data recorded in eyes-closed, eyes-open, and PVT conditions, a large feature set including PSD and ERP-related features were extracted and selected for predicting RT in the PVT task. Data from the PVT condition achieved the maximum correlation coefficient of 0.81 across all subjects. Data from the resting conditions with a shorter length also obtained high correlation coefficients (eyes-closed: 0.65, eyes-open: 0.50). These results demonstrate the feasibility and robustness of the proposed fatigue monitoring method. Future work will focus on classification algorithms [8], integration of EEG and EOG [13], and evaluation of the prediction error of RT [14] to better estimate mental fatigue towards practical applications.

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