Evaluation of Mental Workload in Visual-Motor Task: Spectral Analysis of Single-Channel Frontal EEG

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***Abstract*—This study explores the feasibility of mental workload monitoring using a single-channel mobile EEG system. We investigated the modulation of frontal neural activity with respect to changes in mental workload levels induced by visual-motor tasks of varied difficulty. Using a computerized visual-motor task similar to mirror drawing, our work demonstrated that perceived difficulty was more dominated by the complexity of the path to be traced than the actual time taken to complete the task. EEG activities recorded from the forehead area at the beginning of each trial are positively correlated with overall perceived difficulty of the task. Results in this study suggest that frontal EEG spectra are significantly modulated by the changes in relative mental workload levels during a visual-motor task. Such finding shed light on the possibility of mental workload monitoring in daily life using a user-friendly mobile EEG system.**

Keywords—Homecare and remote patient monitoring; mobile telehealth and wireless applications; telehealth software and systems; evaluation of mental workload.

I. Introduction

Advancement in information technology and automation in work and home environment have brought dramatic changes to our daily life in the last twenty years. Cognitive demand rather than physical were required at work due to the dissemination of computers and intelligent machines. Everyday, we live with overwhelming information from our mobile devices and computers, and spent excessive amount of time operating machines or computers. Such excessive demand of mental workload might lead to extreme consequence in personal health. The link between mental and physical health is well recognized [1]. While new technologies have been developing to monitor various indices of physical health, such as heart-rate, blood pressure and body temperature with wearable and wireless devices [2-4], the options for mental workload monitoring are much more limited. One of the major challenges is the complication in measuring and quantifying mental states objectively. Recent neuroscience research is working on narrowing the gap with sophisticated brain imaging techniques, including the electroencephalography (EEG) and functional magnetic resonance imaging (fMRI). However, these experimental techniques require lengthy and complex set-up. Measurements can only be conducted within a well-controlled laboratory environment, which restricted their everyday application in mental state monitoring.

Recently, different working prototypes of mobile EEG system have been proposed. Most of these proposed mobile EEG systems offer a wireless and easy-to-use solution for users to monitor their real-time brain activities while maintaining the high temporal resolution of signal obtained by traditional laboratory EEG systems [5-10]. The EEG signal collected from such mobile devices was shown to be useful in quantifying users' mental states [11]. In light of this, this study set out to explore a mental workload monitoring solution with a single-channel dry sensor mobile EEG system. Relative to the conventional wet EEG system which comes with various technical difficulties such as skin and electrode preparation, users' discomforts and lengthy preparation time, the ergonomic design and high mobility of the dry sensor EEG system enable us to evaluate the mental state of users during an unconstrained natural task, in a real world setting outside the laboratory.

Mental workload level varies according to the task difficulty and complexity and it reflects how well a person can master a specific task [12]. Previous works have explored the use of EEG in mental workload assessment and have reported a relationship between mental workload and changes in EEG band oscillations [13-15]. A study in early 1980s showed that frontal midline theta activity appeared most frequently in difficult blocks of a tracking task [16]. Laukka et al reported similar finding in theta activity in a simulated driving task [17]. More recently, Kottlow *et al* observed the power of EEG oscillations at the right occipitoparietal and central frontal areas in the upper alpha frequency range was significantly lower in experienced artists than in novices during drawing and related tasks [18]. However, most of these studies employed multi-channel wet EEG systems and/or event-related potential measurements under well-controlled, structural paradigm settings, making technology transfer in everyday environment infeasible.

In contrast with the previous multi-channel EEG studies in mental workload, the present study adopted a single-channel approach. Concurrent monitoring of brain activity during a visual-motor task was performed by a single-channel dry sensor EEG system. Different levels of mental workload were assessed with mirror-drawing tasks of varied difficulty levels. The collected EEG signal was analyzed with different signal processing techniques and the results of the analysis were compared systematically. The results of this study have demonstrated the feasibility of mental workload monitoring using an user-friendly mobile EEG system, encouraging further exploration and development work along this direction, leading to potential telehealth and wireless applications which address the mental health concern in our daily life.

II. Methods

A. Experiments

Ten volunteers (age: 26±3 years; male/female: 7/3) were recruited in this study. All the participants have normal or corrected-to-normal vision and have no history of neurological or psychological disorder. Participants received informed consent to the experimental procedure, which was approved by the ethics committee at the City University of Hong Kong.

Participants completed 8 trials of a computerized visual-motor task similar to mirror drawing. The mirror drawing task was first used by Milner to assess the impact of memory impairment on acquiring a new motor task [19]. To complete the task successfully, participants were required to acquire a new set of visual-motor associations (i.e., moving their hands to the opposite direction as showed on the screen) and to suppress the well-learned association between vision and motor control [20]. In the present study, participants were asked to complete a computerized task similar to mirror drawing which is programmed with the PsychToolbox in MATLAB [21-23]. In each trial, participants were required to trace the boundary of the presented figures as in Fig. 1 with a mouse. The program reversed the left and right movement of the mouse. Participants were asked to keep holding on the left key of the mouse through the tracing and the tracing was stopped when the participants released the key. Subjects were given 8 practice trials to get familiarized with the task before the data collection. In each data collecting trial, participants were required to complete the tracing within 5 minutes. Participants were reminded to trace within the boundary as accurate as possible and should go back to the boundary at the same location where the tracing left the boundary. At the end of the trial, participants were asked to rate the difficulty level of the tracing using a visual analogue scale from 1 to 7, representing "not difficult at all" to "extremely difficult".

B. Data Collection

Two separate computers controlled the drawing task and the EEG data collection respectively. Clock synchronization was performed before each experiment. The drawing task was presented to the participants with a 24" LCD monitor which was positioned 24" from the forehead of the participants. Behavioral data including the completion time (i.e., the time from the first cursor movement to the last detected movement), completion rate (i.e., the percent of drawing that the subject completed), accuracy (i.e., the percentage of drawing the subject made within the boundary of the presented image), and subjective rating of task difficulty were collected together with the actual tracing path by the MATLAB program. Single-channel EEG data were collected from forehead area of subjects using the NeuroSky MindWave Mobile headset at a sampling rate of 512Hz. EEG data were transmitted wirelessly, and stored to the data collection computer during the experiment.

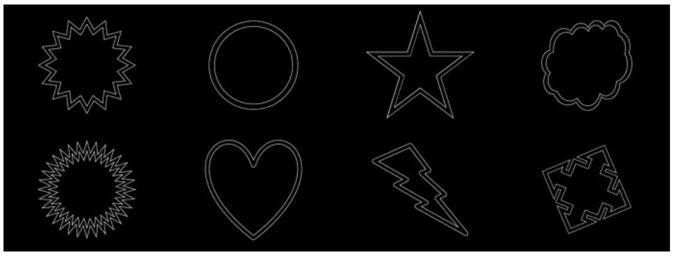


Fig. 1. The eight figures presented in the drawing task. First row: Trial 1-4 (from left to right); Second row: Trial 5 - 8 (from left to right).

C. Data Processing and Analysis

Raw EEG signals sampled at 512Hz were detrended and those between 0.5 to 45 Hz were extracted. Wavelet-based filter was then applied to the data to remove eye blink and movement related artifacts [24]. Continuous EEG was segmented into epoch based on mouse cursor movement onset and offset time. Short-time Fourier transforms over 50% overlapped 2s Hamming windows were computed for all pre-processed EEG segments. Average power spectra were then computed across segments for each trial performed by individual subjects. Task-related spectral power variations were investigated within eight frequency bands (Delta: 1-4Hz; Theta: 4-8Hz; Lower Alpha: 8-11Hz; Upper Alpha: 11-14Hz; Lower Beta: 14-25Hz; Upper Beta: 25-36Hz; Lower Gamma: 36-40Hz; Upper Gamma: 40-44Hz).

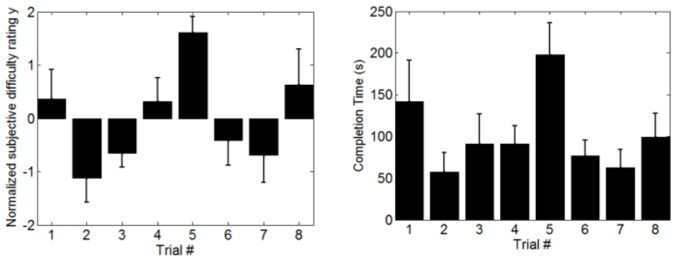
To reduce the between-subject effect, subjective difficulty index x_{ij} was transformed to normalized rating y_{ij} using

$$y_{ij} = \frac{x_{ij}-\mu_j}{\sigma_j} \quad (1)$$

where x_{ij} is the difficulty level reported by subject j in trial i; μ_j is average of difficulty ratings reported by subject j; and σ_j is standard deviation of the subjective difficulty ratings reported by subject j. We would then explore the relationship between EEG frequency band activities with the normalized subjective difficulty ratings. To further explore the timely relationship between the perceived difficulty and EEG activity, the EEG data were segmented into 30s segments for additional correlation analysis. Offline analyses comparing statistical models comprised of all possible combination of prominent EEG features selected from preceding analyses were performed to establish an optimal model for mental workload monitoring.

III. Results

Fig. 2 illustrated the average normalized subjective difficulty rating and the completion time of each trial. In general, most subjects found Trial 5 to be the most difficult task, and Trial 2 to be the easiest. Correlations of normalized perceived difficulty rating with the path length, number of angles in the path, and the time taken to finish each trial were 0.7714, 0.8007, and 0.6704 respectively ($p < 0.001$). Number of angles in the path corresponds to the number of sharp changes in path direction involved. No notable linear relationship could be observed between the normalized subjective difficulty rating and the average speed of individual subject in completing each trial. The accuracy in tracing was also found to be unrelated with the time and speed in current experiments.



(a) (b)

Fig. 2. Average (a) normalized subjective difficulty ratings and (b) time taken to complete each trial.

The results shown in Table 1 indicated that the average EEG power in upper alpha band, but not the power in other bands of EEG, of whole trial had a significant positive correlation with the perceived difficulty of individual subject. Drawing accuracy was also unrelated with the band powers of EEG at the forehead area throughout whole trial.

TABLE I. RELATIONSHIPS BETWEEN AVERAGE BAND POWERS AND INDIVIDUAL OUTPUTS IN EACH TRIAL

Band	Correlation with average band power	
	Subjective Difficulty	***Performance Accuracy***
Delta	0.1222	-0.0056
Theta	0.1112	0.1118
Lower Alpha	0.1849	0.0518
Upper Alpha	**0.2392***	-0.0337
Lower Beta	0.1201	0.1441
Upper Beta	0.0491	0.1504
Lower Gamma	0.0195	0.1288
Upper Gamma	0.0360	0.1071

*Statistical significance at $p < 0.05$.

To investigate if EEG power spectra vary with the experimental time, the relationship between time and the individual band power was evaluated every 30 seconds for all trials as shown in Table 2. Band power of frequency components over 14Hz was higher at the beginning of the experiments and gradually decreases in the first 30s of the trials. No significant EEG spectral trend was observed in 90-150s and 180-210s from the start of the trial. In short, EEG power spectra, except theta and lower alpha activities, were time-varying in this experiment. For example, upper alpha activities were only related to time after 30s of trial.

TABLE II. RELATIONSHIP BETWEEN TIME AND BAND POWER

Band Power	Correlation with time				
	First 30s	***30-60s***	***60-90s***	***150-180s***	***210-240s***
Delta	0.004	0.034	**0.055***	0.019	-0.084
Theta	-0.007	0.037	0.018	-0.026	-0.029
Lower Alpha	0.029	0.029	-0.013	-0.002	-0.017
Upper Alpha	-0.025	**0.069*****	0.001	**0.115***	0.097
Lower Beta	**-0.045***	**0.060****	0.037	-0.076	-0.068
Upper Beta	**-0.092*****	0.035	**0.083****	-0.028	**-0.278****
Lower Gamma	**-0.105*****	**0.045***	0.015	-0.035	-0.150
Upper Gamma	**-0.108*****	0.038	0.041	0.056	-0.104

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Inasmuch as the EEG power spectra were time-varying, relationship between data collected from different time segments and overall perceived difficulty was evaluated as shown in Table 3. Both frontal theta and alpha power demonstrated positive relationships with the perceived task difficulty in the first 30s, but their significance decreased with time, especially theta power. EEG activities are indicative of subjects' perceived difficulty during visual-motor task only in the first 30 seconds of each trial but not data collected afterwards probably because of other temporal factors introduced to the subjects or induced by themselves.

TABLE III. RELATIONSHIP BETWEEN SUBJECTIVE DIFFICULTY AND EEG FEATURES OF INDIVIDUALS IN DIFFERENT TIME SEGMENTS

EEG Features	Correlation with subjective difficulty		
	First 30s	***Mid-30s***	***Last 30s***
Delta Power (Delta)	0.1350	0.1244	0.1243
Theta Power (Theta)	**0.3002****	0.0984	0.0492
Lower Alpha Power (Alpha1)	**0.3208****	0.1075	0.0847
Upper Alpha Power (Alpha2)	**0.3329****	0.1439	0.1790
Lower Beta Power (Beta1)	0.1663	0.1259	0.1607
Upper Beta Power (Beta2)	0.1057	0.0180	0.1128
Lower Gamma Power (Gamma1)	0.0358	0.0075	0.0924
Upper Gamma Power (Gamma2)	0.0849	0.0579	0.0993

**$p < 0.01$.

The average power spectral densities of EEG activities in the first 30s are shown in Fig. 3 and Fig 4, which visualize the power spectra of EEG data recorded in trials with normalized subjective ratings above and below 0 respectively. The most difficult task in the experiment induced the maximum changes in initial EEG activities within the theta band. However, in slightly less difficult trials, theta activities decreased significantly. In contrast, the power spectral densities of the significantly more difficult trials showed that their upper alpha activities remained higher than those in the easier trials. These results also agree with the previous statistical analysis.

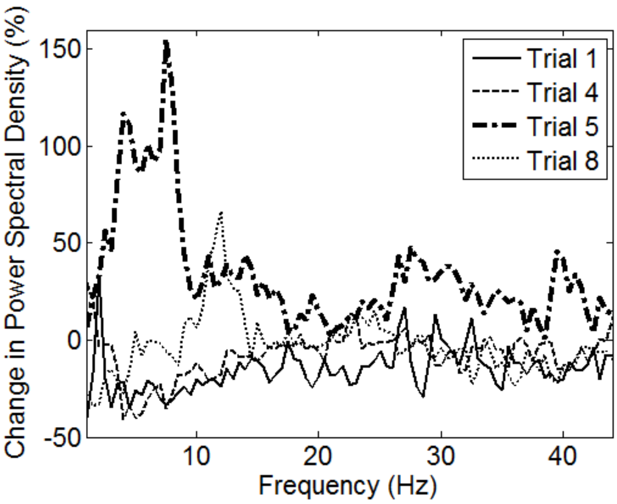


Fig. 3. Percentage changes in average power spectral density with respect to the overall mean activities in the first 30s of the relatively more difficult trials. Trial 5 is the most difficult trial. Trial 8 is relatively less difficult than Trial 5. Trials 1 and 4 are indifferent to the averge subjective difficulty rating of all trials in the experiments statistically.

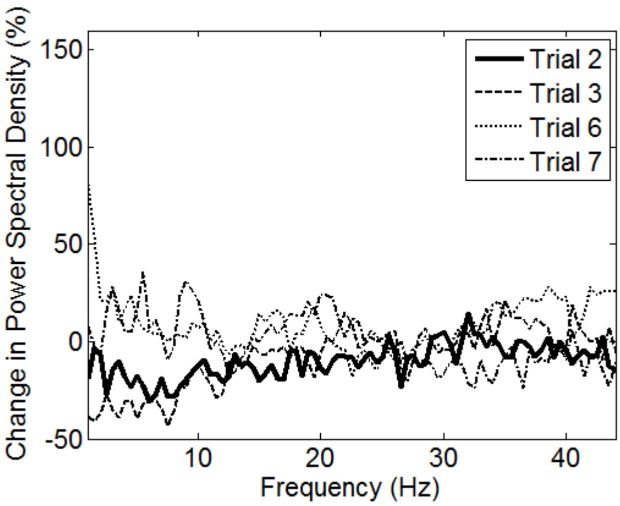


Fig. 4. Percentage changes in average power spectral density of the relatively easier trials with respect to the overall mean activities in the first 30s. Trial 2 is the easiest trial. Trials 3 and 7 are slightly more difficult than Trial 2. Meanwhile, the average difficult level of Trial 3 has a much higher statistical confidence than that of Trial 7. Trial 6 is close to the average difficulty level of all trials in the experiment.

Using results from preceding analyses as shown in Table 3, all possible combinations of theta power, lower alpha power and upper alpha power in the first 30s were used to build 7 linear regression models in order to predict the mental workload level from EEG signal collected. The performances of the models, expressed as normalized root mean squared error (NRMSE), were assessed through a 10 fold cross-validation. Figure 5 summarized the offline analysis results comparing the seven models comprised of each possible combination of theta power, lower alpha power and upper alpha power in the first 30s. Our results indicated that statistical model constructed using upper alpha alone outperformed the other models in terms of NRMSE.

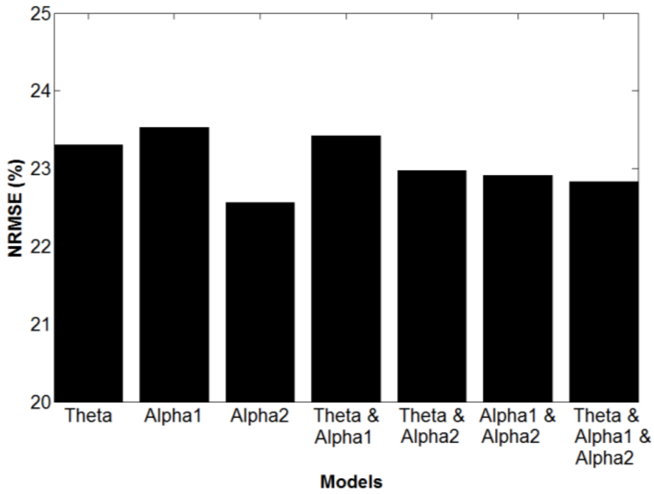


Fig. 5. Offline analysis results comparing models comprised of all possible combination of selected features (Theta, Alpha1, and Alpha2 in first 30s). Model performance were expressed as normalized root mean squared error between the actual and predicted value, averaged across the 10 validation groups.

IV. Discussion

The finding of this study found significant relationship between spectral features of single-channel frontal EEG and levels of mental workload required by the task. From the experimental results, consistent increase in EEG activities in upper alpha band (11-14Hz) was induced by significant increase in mental workload. The connection between frontal EEG activities and mental workload is particularly significant in the first 30s of each trial. It is possible that other temporal factors happened after the first 30s contributed to this finding. Our results also indicated that mental workload level associated with the task was more dominated by the number of sharp directional changes involved in the trace than the actual time taken to complete the task.

Relationships between theta and alpha signals with difficult and effortful tasks had been reported frequently [14, 16, 17, 25-27]. Specifically, Gevins and Smith reported an increased frontal theta power and decreased parietal alpha power during high-load task [26, 27]. From our results, both frontal theta and alpha power demonstrated positive relationships with mental workload. Such relationship in theta was in accordance with previous findings but it was only statistically significant at the beginning of the most difficult trial. It is possible that the opposing finding in alpha power between our study and works by Gevins and Smith is related to the difference in recording positions, Fz and Pz.

Among all linear models that could be built using these three key features (Theta, Alpha1, and Alpha2) in logarithmic scale, the model with Alpha2 extracted from the initial data offered the lowest mean squared error in cross-validation. This suggests that Alpha2 is a significant neural activity indicator, which can be used to estimate the level of mental workload to be incurred to each user based on frontal EEG collected at the beginning of the task. The statistical model derived will assist telehealth and wireless application developers to deliver optimal real-life solutions by quantifying or estimating the mental workload induced by the usage of these applications.

One of the common concerns in the studies of this area was the possible overlap of difficulty and practice effects. In this study, attempts were made to minimize such effect. Subjects were asked to have 8 practice trials of the mirror drawing task and were familiar with the task before proceeding to the mental workload experiment. Also, the sequence of trials with different levels of difficulty was arranged in a pseudo-random order.

Thus far, we revealed the EEG correlate of mental workload in a relatively simple motor task using some of the most commonly used EEG features. Further work has to be done to enhance the model performance by more sophisticated signal processing and feature extraction methods. Also, we will repeat the experiment with mental task and possibly with additional EEG features. It is possible that a different set of EEG features would be found due to the different nature and neural activation pattern between motor and mental tasks.

ACKNOWLEDGEMENT

This work has been supported by industrial sponsorship from NeuroSky (Hong Kong) Co. Ltd., HKIEd (internal grant no. RG65/11-12), the Innovation and Technology Fund (ITS/074/12FX) provided by the Innovation and Technology Commission, HKSAR. Any opinions, findings, conclusions or recommendations expressed in this material/event (or by members of the project team) do not reflect the views of the Government of the Hong Kong Special Administrative Region, the Innovation and Technology Commission or the Panel of Assessors for the Innovation and Technology Support Programme of the Innovation and Technology Fund.

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