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Frontal Theta EEG Dynamics in a Real-world Air Traffic Control Task*

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Abstract — **Mental workload and time-on-task effect are two major factors expediting fatigue progress, which leads to performance decline and/or failure in real-world tasks. In the present study, electroencephalography (EEG) is applied to study mental fatigue development during an air traffic control (ATC) task. Specifically, the frontal theta EEG dynamics are firstly dissolved into a unique frontal independent component (IC) through a novel time-frequency independent component analysis (tfICA) method. Then the temporal fluctuations of the identified frontal ICs every minute are compared to workload (reflected by number of clicks per minute) and time-on-task effect by correlational analysis and linear regression analysis. It is observed that the frontal theta activity significantly increase with workload augment and time-on-task. The present study demonstrates that the frontal theta EEG activity identified by tfICA method is a sensitive and reliable metric to assess mental workload and time-on-task effect in a real-world task, i.e., ATC task, at the resolution of minute(s).**

I. Introduction

Mental fatigue is a gradual and cumulative brain process linked to decreased sustained attention, reduced effort, and impaired performance efficiency or even failures [1]. It is believed that mental fatigue is a major hazard of accidents or injury when driving or when performing tedious and/or repetitive tasks for a long time. Air traffic control (ATC) task is a complicated cognitive task, which requires operators to focus on task for long time in a dimmed-light environment. The operators likely become fatigue due to accumulated workload [2] and/or time-on-task [3]. Therefore, it is of fundamental significance to assess and measure operators' mental workload and/or time-on-task effect. Accurate monitoring of mental workload and/or time-on-task effect is helpful to predict performance decline and further prevent the occurrence of catastrophic loss.

Among the many psychological and psychophysiological measurement methods, electroencephalography (EEG) that directly measures the functions of central nervous system has been validated as a sensitive and reliable means to assess mental processes [4-8]. Lots of EEG indices from different frequency bands and brain regions have been proposed to measure mental workload or fatigue [5, 9]. Among such EEG indices, frontal theta activity is reported to have a robust increase as the mental effort, workload augment, time-on-task effect, and fatigue processing [5, 8, 9]. The frontal theta activity is also observed in many cognitive tasks that require concentration, attention, conflict monitoring, performance monitoring, and working memory with its neural substrates in prefrontal cortex, specifically in anterior cingulate cortex (ACC) [10-15]. Such cognitive functions are vital in ATC tasks. Taken all together, the present study focuses on the frontal theta EEG activity, and its sensitivity as a measure metric for mental workload and/or time-on-task during an ATC task simulated in CTEAM V2.0 [16] are investigated.

Unfortunately, EEG signals are very weak and always contaminated by ocular and muscular activations. Also, EEG signals measured on the scalp are generated from multiple neural sources that perform different cognitive functions. Moreover, in ATC tasks, EEG is continuously recorded with no repetitive well-defined events/stimuli as those in classic cognitive tasks. Therefore, it is not easy to characterize the frontal theta activity by directly selecting one or several specific channels, such as channel FCz. Furthermore, the requirement of time resolution in the assessment of workload in real ATC tasks is not as high as that in cognitive studies (i.e., millisecond). Hence, in the present study, a novel time-frequency independent component analysis (tfICA) is implemented and applied to disentangle the frontal theta activity into ICs with one second resolution. In our previous study [17], the tfICA method has been validated as a useful method to probe neural activations in the continuous EEG signals. After obtaining the frontal ICs, their spatial and spectral patterns are examined. Then the spectral fluctuations of frontal ICs are investigated against workload levels reflected by behavioral data (i.e., number of clicks per minute), and the time-on-task effect.

II. Material and Methods

A. Subjects and experiment

Eleven subjects (all males, ages: 25±4.3), recruited at University of Oklahoma, participated in this study after obtaining their written informed consent. The experiment protocol was approved by the IRB committee of the University of Oklahoma.

Subjects performed an air traffic control task, simulated in software C-Team V2.0 [16]. A typical scenario of the operational interface can be seen as Fig. 1 in [17]. Subjects were required to safely navigate the airplanes to the assigned destinations (i.e., airports or exits), by adjusting the heading direction, speed and level on the command panel using a mouse (see Fig. 1 in [17]). The entire experiment included one training session (0.5 hour), and two recording sessions (of 1 hour each). The three sessions were conducted on different days. The behavior performance including number of warnings, number of crashes, number of clicks per minute and activation time for each airplane were analyzed in 21 sessions (one session's behavior data was not recorded) [17].

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The behavioral data indicated that all subjects give their best performance during the task. For more details about the experimental and behavioral data, please refer to [17].

B. EEG acquisition and preprocess

A 128-channel Net Amps 300 amplifier (Electrical Geodesics Inc. OR, USA) was used to record EEG signals with sampling frequency of 250Hz and the reference channel at Cz. EEG data were offline downsampled to 125Hz and band-pass filtered (i.e., 0.2~30Hz). Infomax ICA from EEGLAB toolbox [18] was performed on processed EEG data to remove artifactual ICs related to ocular, cardiac and muscular activities. The residual EEG signals were used for further analysis.

C. Time-frequency independent component analysis

A novel tfICA method was adopted to disentangle the frontal theta EEG activity from mixed EEG signals into a unique IC [17]. The tfICA method integrated time-frequency analysis and ICA model to explore the independence of neural sources in both temporal and spectral domain. Preprocessed EEG signals were firstly transformed into spectral domain by short-time Fourier transformation with a one second Hanning window to obtain the time frequency representation (TFR) of EEG signals with the dimension as ($N_c \times N_t \times N_f$: N_c is the number of channels (i.e., 128), N_t is the number of windows (i.e., 3600), N_f is the number of frequency bins (i.e., 64)). The three dimensional (3D) TFRs of EEG were further arranged into two dimensions (2D) as ($N_c \times (N_t \times N_f)$) by selecting the frequency bins from 5 to 30 Hz. After replacing outlier segments that exceeded 3 times standard deviation with neighboring 'good' segments, the 2D TFR complex-valued data were decomposed into 25 ICs by a complex-valued ICA model [19]. More details about tfICA method were described in [17].

D. Frontal ICs

From the 25 ICs calculated by tfICA method, the one with the most typical frontal spatial pattern and theta spectral pattern were selected as the frontal IC to represent the frontal theta EEG activity. One frontal IC was selected from each session data except two sessions (S8s1 and S10s2), where the frontal IC was not detected. For these two sessions, the frontal theta IC spatial pattern from the other session within the same subject was adopted and the temporal-spectral patterns were calculated accordingly. After identification of frontal ICs, the spatio-temporal-spectral characteristics of the frontal theta EEG activity were probed as follows:

1) The neural generators of frontal theta activity were located by a dipole source based inverse problem solution using the DIPFIT function in EEGLAB with MNI template head model [18]. Since the obtained mixing matrix is complex-valued [17], a further transformation as that in [20] was performed to move the phase shift information to imaginary part of complex-valued mixing matrix and the real-part of the transformed mixing matrix was used for the source localization.

2) The frontal theta activity was compared to concurrent task workload indexed by number of clicks per minute since all navigation commands were performed by mouse clicks: a) the power spectrum densities (PSDs) of frontal ICs from high workload (one second segments in which number of clicks larger than median value of number of clicks per session) and low workload (one second segments in which number of clicks less than median value of number of clicks per session) was statistically compared for individual frequency bin across sessions (i.e., 21 sessions) and subjects (i.e., 11 subjects); b) The theta (5 to <8Hz) dynamics of frontal ICs were further correlated to number of clicks per minute by a Pearson correlation analysis; c) the linear regression models were built on the mean theta activities of one minute by sorting the theta activities with number of clicks per minute in ascend order for every session.

3) The frontal theta dynamics was compared to time-on-task on a minute scale: the workload related effect was firstly subtracted from the original rhythmic theta activities by the trained linear regression model with number of clicks per minute. Then another linear regression analysis was conducted on the remaining theta activities to test whether the frontal theta dynamics is significant reflecting the time-on-task effect.

III. RESULTS

A. Spatial and spectral patterns of frontal ICs

The spatial and spectral patterns of the frontal ICs identified from each session were illustrated in Fig. 1. It can be seen that 20 ICs were identified from 22 sessions except two sessions, i.e., S8s1 and S10s2. The frontal ICs have the evident spatial patterns as a focal distribution in the frontal area (magnitude of mixing matrix in Fig. 1 (A) and real-part of mixing matrix in Fig. 1 (C)), and evident theta peak in the spectral patterns (Fig. 1 (B)). The spatial and spectral patterns were more similar within the subject than across the subjects. Furthermore, the neural generators of frontal ICs were localized from the real part of the spatial patterns (Fig. 1 (C)) and displayed in Fig. 1 (D). A single dipole source can well

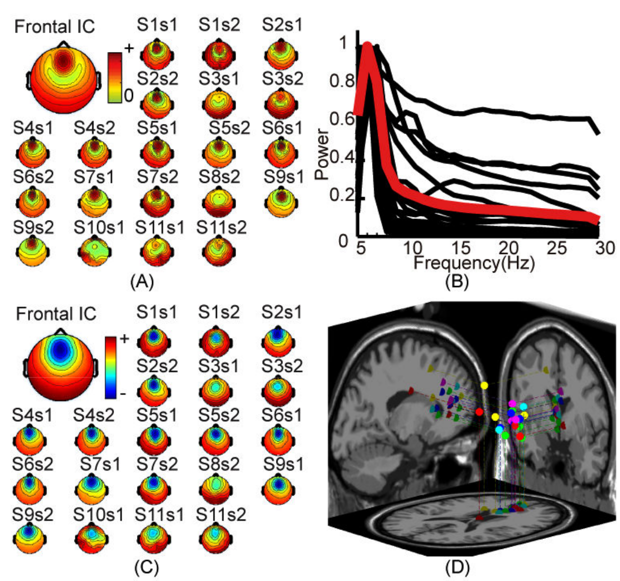

Figure 1. Frontal ICs identified from two sessions in all subjects: (A) individual scalp maps of magnitude for different sessions with the averaged one on the top right corner, (B) individual normalized spectra with the averaged one as the red curve, (C) individual scalp maps of transformed real-part mixing matrix with the averaged one on the top right corner, (D) 3-D dipole source locations (colored spheres for different sessions) and their projection to the MNI template head images. Labels above each plot in (A) and (C) represent subject number ('S1' denotes subject #1) and session number ('s1' denotes session #1).

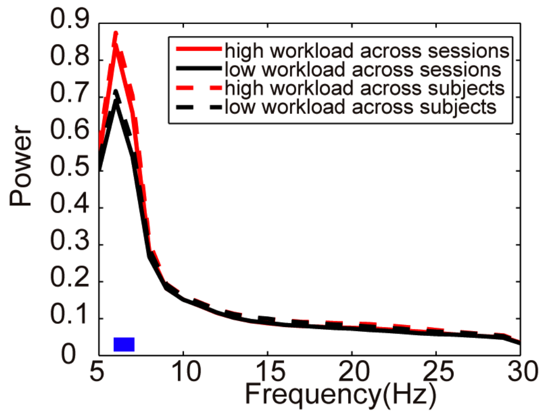

Figure 2. The averaged PSDs of frontal ICs from high and low workload levels across sessions and subjects. Blue horizontal line denotes the frequencies exhibiting significant power difference (p<0.01 across subjects and p<0.001 across sessions).

explain the spatial distribution of frontal ICs with the mean residual variance as 4.6% (SD: 3.5%). The dipole sources were located in the vicinity of ACC with the mean Talairach coordinate as (-1, 32, 10) (Brodmann area 24).

B. *Effect of workload*

The averaged PSD of the frontal ICs for different workload levels were plotted in Fig. 2. The t tests across 21 sessions and 11 subjects revealed that the powers at 6 Hz and 7 Hz frequencies (i.e., theta band) significantly increased at the high workload level relative to low workload level (p<0.001 across sessions and p<0.01 across subjects). These observation were further corroborated with the correlation analysis of rhythmic theta activities and number of clicks per minute. Positive correlation coefficients in theta activities were identified in 20 sessions, in which 16 sessions reached significant level (p<0.05). Such phenomena were not observed in alpha (8 to <13Hz) and beta (13 to 30Hz) band activities of frontal ICs (alpha: 14 positive (6 significant) and 7 negative (3 significant); beta: 15 positive (4 significant) and 6 negative (3 significant)). The linear regression analysis also revealed 20 positive slope linear regression models of theta activities with the increased number of clicks with 15 sessions within significant level (p<0.05). Both detections of significant positive correlation coefficients and positive slope regression models were significant in terms of binomial test (p<0.01 for correlation and p<0.05 for regression). The missed detections of significant positive values happened in S7s1 and both sessions of S10 and S11.

C. *Temporal dynamics with time-on-task*

The regression analysis results of the theta temporal activities from frontal ICs of 21 sessions after the subtraction of workload related frontal theta dynamics were displayed in Fig. 3 (A). Similar to the session performance of significant correlation with number of clicks, positive slope regression models were identified in 19 sessions, in which 14 reached significant level (p<0.05). This detection was also significant (p<0.05). The missed detections happened in S8 in addition of those sessions with missed detections in correlation with workload.

In comparison, the regression analysis results of the original theta activities (without removing the effect of workload) with time-on-task were displayed in Fig. 3 (B). Although it had similar detection of positive (significant) slope regression models (19(12)), the session performance were very different. If four sessions from S10 and S11 were excluded as no significant relationships between frontal theta activity and workload within these sessions, the detection of significant positive slopes would decrease to 8, which was insignificant (p=0.8).

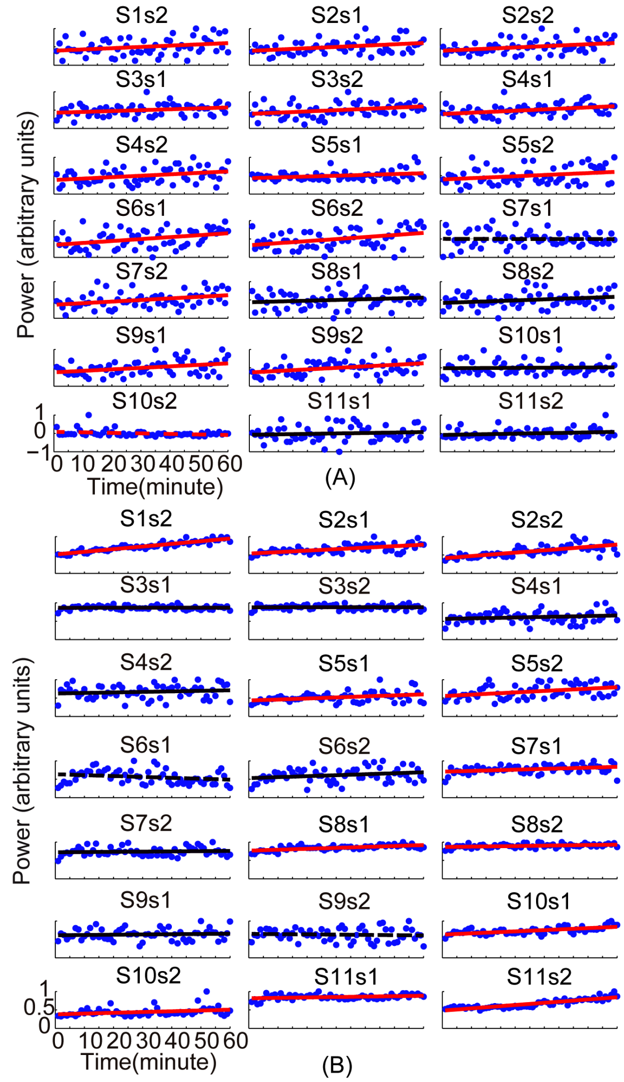

Figure 3. Linear regression analysis of theta temporal dynamics of frontal ICs in 21 sessions after (A) and before (B) subtracting workload effect. In each plot, the dots represent the IC's normalized theta activities in one minute, the line is the trained regression model whose color indicates the significance of slope (red: p<0.05), and the dashed line denotes negative slope while solid one denotes positive slope.

IV. Discussion

In the present study, the dynamics of frontal theta EEG activity is investigated in a realistic ATC task. To dissolve the frontal theta activity from the mixed EEG signals, a novel tfICA method is applied. It is seen that frontal ICs can significantly detected by the tfICA method, and the neural substrates of identified frontal ICs are located into the ACC area, which is consistent with literatures [10, 13, 14]. It reflects the nature of ATC tasks, which require ATC operators to make continuous cognitive effort to navigate airplanes, optimize their navigation routines, and monitor airplanes to avoid crashes.

Though the appearance of airplanes was fixed in the present ATC task (i.e., two airplanes per minute), the instantaneous workload changed due to different navigation strategies used by individual operators. Therefore, we evaluate the instantaneous workload by number of clicks per minute, which reflect the operators' mental effort to meet the requirement of the fluctuated workload. From the identified frontal ICs, spectral power in theta band is observed to be significantly larger in high workload than that in low workload, which is in agreement with previous studies [5, 8, 9, 15]. Moreover, the significant detections of significant positive correlation and significant positive slope regression models between rhythmic theta activities and number of clicks indicated that the frontal theta activity is a sensitive and reliable metric to assess the workload levels during an ATC task.

Two kinds of linear regression analysis between rhythmic theta activities and time-on-task were performed in the present study. It can be seen that both regression models reveal larger number of significant positive slopes as compared to negative slopes, which indicates that frontal theta EEG activity increase with time-on-task, which is also consistent with previous studies [5, 7-9]. While these two regression models had significant difference and the one after the removal of workload effect is more consistent with the performance in detecting workload effect from frontal theta activity (i.e., the missed detections of significant relationships are mainly happened in same subjects, i.e., S10 and S11). Meanwhile, the significant relationship between frontal theta activity and workload implies the frontal theta activity is largely influenced by workload. Therefore, it can be concluded that such factors, e.g., workload, are better to be removed when the time-on-task effect is investigated by EEG signals, and the frontal theta activity is a sensitive and reliable metric to assess the time-on-task effect during ATC tasks.

In the present study, missed detections of significant relationship between frontal theta activities and workload/time-on-task occurred in some sessions. One possible reason may be that the frontal IC is not well decomposed due to the noise, e.g., missed decomposition in S8s1 and S10s2, and more than one decomposition of frontal theta activity in both sessions from S11. Therefore, more efforts are needed to identify the "good" frontal ICs by further discarding artifacts like electromyogram (EMG).

In conclusion, the present study justified that the frontal theta EEG activity is a sensitive and reliable metric to assess workload and time-on-task effect during an ATC task at the resolution of minute(s). It also demonstrated the potential capability of tfICA method in probing neural activations from continuous EEG in real world tasks. As a following work, the tfICA method will be applied to analyze EEG signals recorded in real field where the experienced ATC officers perform a high fidelity ATC task.

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