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EEG Correlates of Fluctuation in Cognitive Performance in an Air Traffic Control Task

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16. Abstract

Performance changes that are attributed to mental fatigue in real-world tasks need reliable monitoring to prevent occupational hazards. The present study investigated the association of cognitive functional decrements over time with neurophysiological patterns indicative of mental fatigue when performing a low-fidelity simulated air traffic control task for up to two hours. Electroencephalography (EEG) and performance data, i.e., response time and routing time for navigating aircraft, were simultaneously collected during the task.

Cognitive capacities of participants were assessed using the Minicog rapid assessment battery before and after the task. Acquired EEG signals were epoched into multiple segments of 10 minutes over time, and these segmented EEG data were statistically compared with each other using non-parametric statistical analysis to identify neurophysiological patterns due to the time-on-task effect. Significant changes in EEG power spectra were localized to the midline regions from the frontal and parietal areas of the human brain. Significant changes in performance data were also observed in response time and routing time.

These observed changes in EEG power spectra and performance data suggest a consistent correlation among them in the time domain in individual sessions and participants, as well as at the group level. Both deteriorating cognitive performance and EEG, indicative of the development of mental fatigue, occurred at approximately 70 minutes into the task. Such a correlation suggests EEG signals are promising for use in developing a reliable on-line mental fatigue monitoring system.

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Contents

EEG Correlates of Fluctuation in Cognitive Performance
in an Air Traffic Control Task

EEG CORRELATES OF FLUCTUATION IN COGNITIVE PERFORMANCE IN AN AIR TRAFFIC CONTROL TASK

INTRODUCTION

Mental fatigue, defined as the inability of the human brain to allocate sufficient resources to perform a task at normal capacity (Smit, Eling, & Coenen, 2004), can impair a variety of cognitive functions that are vital in performing a task effectively (Bills, 1931; Lorist, Klein, Nieuwenhuis, De Jong, Mulder, & Meijman, 2000; Sanders & Hoogenboom, 1970). Hence, it is desirable to study the effects of mental fatigue and its impact on human performance and work routines. Mental fatigue that happens after hours of work, known as the time-on-task effect, can significantly impact vigilance (Mast & Heimstra, 1964; Smit et al., 2004), problem solving capability (Horne, 1988; Van der Linden, Frese, & Meijman, 2003) and situational awareness (Vidulich, Stratton, Crabtree, & Wilson, 1994), which are the basis for completing most real-world tasks successfully. Mental fatigue is of special concern for air traffic control specialists (ATCSs) due to their cognitively demanding workload and public safety factors. Air traffic control tasks require ATCSs to maintain a constant focus with high reliability and to use multitasking capabilities to process information from a variety of sources for considerably long durations (Kallus, Van Damme, & Dittmann, 1999). ATCSs stay in the forefront of air traffic flow control and communicate vital information such as the proximity of other aircraft, the impact of weather, and the status of runways. These tasks require high levels of cognitive ability and endurance to complete. Performing these tasks for long hours can potentially result in mental fatigue that could be a hindrance to task completion. Since these tasks require high reliability to keep the passengers on board safe, understanding how controllers' mental functions are affected is essential to maintaining safety.

Modern physiological measures such as electrocardiography (ECG), respiration, eye blinks, and electroencephalography (EEG) have been proven more reliable and effective in monitoring fatigue (Brookings, Wilson, & Swain, 1996; Han, Wang, L., Wang, P., & Wen, 2005) in real time rather than subjective measures. Among these physiological measures, EEG has been used more extensively in recent times due to its non-invasive nature, high reliability (Lal, Craig, Boord, Kirkup, & Nguyen, 2003; Murata, Uetake, & Takasawa, 2005), and reproducibility (Lal & Craig, 2005). EEG power spectral measures are reported to produce patterns that can be used to identify changes in alertness (Makeig & Inlow, 1993; Makeig & Jung, 1995).

Researchers have identified EEG fluctuations correlated to performance deficits (Jung, Makeig, Stensmo, & Sejnowski, 1997; Kilmesch, 1999; Kilmesh, Doppelmayr, Russegger, Pachinger, & Schwaiger, 1998; Lal and Craig, 2002, 2005; Makeig & Inlow, 1993; Makeig & Jung, 1995). Event-related potentials (ERPs), small blocks of mean EEG phase-locked to the onset of stimuli, have shown significant patterns corresponding to performance change and mental state shift (De Lugt, Loewy, & Campbell, 1996; Pfurtscheller, 1992; Pfurtscheller & Aranibar, 1977; Neuper & Pfurtscheller, 2001). Another way of identifying EEG patterns is by using time-frequency analysis. This method has shown significant increases in alpha and theta powers, time-locked to stimulus presentation (Kilmesch, 1999; Akerstedt & Gillberg, 1990; Torsvall & Akerstedt, 1987).

Most of these research studies on mental fatigue use either event-driven hour-long tasks (Huang, Jung, Delorme, & Makeig, 2008; Jap, Lal, Fischer, & Bekiaris, 2009) or considerably long-duration tasks, focused on effects of monotony or workload changes from EEG data analysis. Only a very few studies have focused on determining the effects of mental fatigue and physiological markers for mental fatigue in real-world work scenarios. In our research, we approached the problem of mental fatigue by correlating the performance changes with EEG patterns that represent the development of mental fatigue over time. We conducted four experimental sessions using simulation tasks from a low-fidelity air traffic control software package, i.e., C-Team (Bailey, Broach, Thompson, & Enos, 1999), with increasing work time, ranging from one half hour to two hours, for determining the amount of change in performance and EEG patterns associated with mental fatigue over time. This provided a better means to understand the effects of fatigue over different intervals of time and their effect on brain functions.

Furthermore, it is essential to determine the relationship between cognitive performance changes and EEG patterns indicative of mental fatigue to develop a reliable method for detecting time-on-task fatigue in real time. To achieve this, we hypothesized that a prominent change in EEG spectral power can be a marker for change in mental state, as reported by other studies (Gevins et al., 1995; Wilson & Russell, 2003). Since our method provides a means for continuous evaluation, our findings can be valuable in the design of continuous fatigue monitoring models, in contrast to earlier neural network models focused on fatigue prediction based on ERPs (Murata et al., 2005).

In summary, we conducted a study to investigate continuous EEG spectral power changes that are correlated with performance change during a low-fidelity air traffic control task. To determine EEG spectral power changes, we conducted a power spectral analysis and implemented a non-parametric statistical approach on the EEG data collected from four experimental sessions (30, 60, 90, & 120 minutes). Next, we computed different performance measures such as response time, routing time, number of crashes, and number of warnings from the C-Team data. A correlation between EEG spectral power changes and performance data was then established by comparing significant changes observed in these data and their occurrences over time.

1

METHOD

Participants

We recruited 10 healthy male participants from the population of students at the University of Oklahoma between the ages of 22 and 30 (Mean±SD = 25±2.3, all right handed) having no prior experience with air traffic control. All participants took part in four recording sessions that lasted for one half-hour, one hour, an hour and a half, and two hours, which will be referred to as Session 1, Session 2, Session 3, and Session 4, respectively, totaling 40 data collection sessions. However, data from Participant 1 (Session 3) and Participant 6 (Session 3) were excluded due to high noise levels that could not be improved by pre-processing using filtering and artifact rejections. All participants took part in the study after giving informed consent according to the University of Oklahoma Institutional Review Board standards. Participants were compensated monetarily for their time.

Experimental Protocol

The Minicog Rapid Assessment Battery (MRAB) (Shephard, Kho, Chen, & Kossyln, 2006) and the C-Team low-fidelity air traffic control simulator (Bailey et al., 1999) were used to study behavioral changes associated with the time-on-task effect (or mental fatigue). Participants performed MRAB cognitive tests before and after recording sessions to identify cognitive performance changes associated with time on task. The MRAB had measures of seven cognitive tasks, including Vigilance, Filtering, Divided Attention, Mental Rotation, Working Memory, Cognitive Set Switching, and Perceptual Reaction.

Vigilance, filtering, and divided attention tasks were used to test the ability of a participant to focus on specific information in order to conduct a task efficiently. The Vigilance task assesses the ability to maintain continuous attention to specific events, the Filtering task assesses the ability to filter out unwanted in-formation, and the Divided Attention task assesses the ability to maintain attention while processing two different types of information. Working Memory investigates the ability to retain information and respond to an event based on information from previous events. Cognitive Set Switching assesses the ability to switch among cognitive sets to process suddenly appearing stimuli in a sequence displaying the same type of information. Mental Rotation requires forming judgments about two geometrical shapes to determine whether they are mirrored images or identical images with rotation. Finally, the Perceptual Reaction Time task is used to check on quickness and accuracy as the stimulus shows up at different locations and corresponding keys must be pushed.

Performance data recorded by the C-Team task were used for the continuous evaluation of fatigue effects with time on task. The C-Team task used for the present study is shown in Figure 1(a). C-Team was run on a PC with Windows operating system, and the operational interface was displayed on a 22-inch monitor. The participants clicked on appropriate controller tabs using a pointing device (i.e., computer mouse) to control aircraft. The participants were required to activate and navigate aircraft that appeared on the display screen at the rate of three per minute. Their goal was to get aircraft to their respective airports or exit gates, as defined on each aircraft data block. The number of aircraft requiring activation was maintained at a constant rate for the entire task. The scenarios were developed in such a way that airport orientation changed every five minutes with a notification that occurred one minute prior to the change through auditory feedback. Proximity warnings were issued whenever aircraft got too close to the boundary edges, airport edges, other aircraft, and restricted areas. Failure to respond to these warnings resulted in a crash.

Figure 1(a) shows the C-Team task display screen, with the aircraft heading to the exit B along the routing path, represented
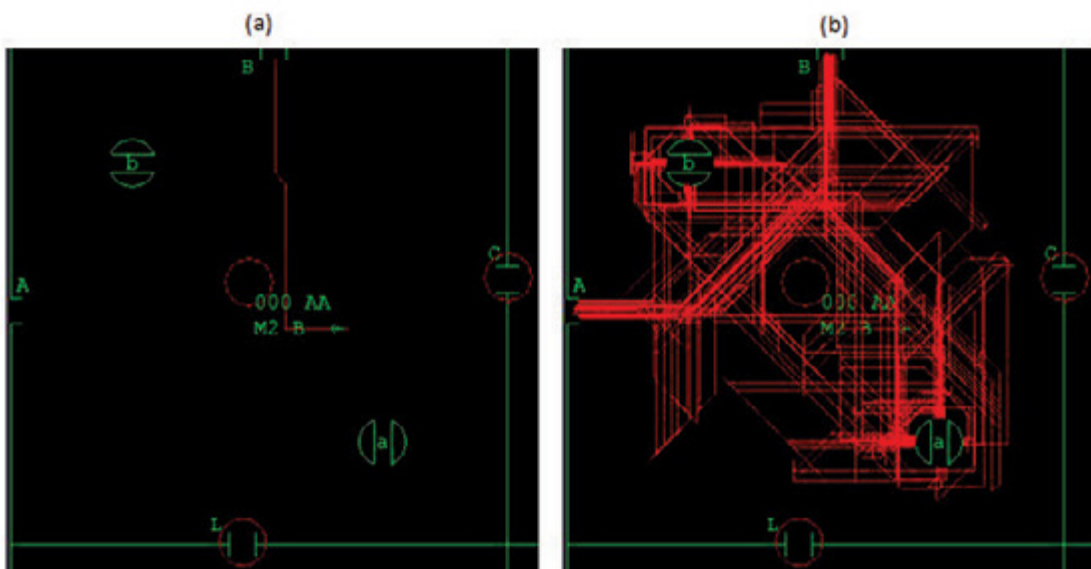

Figure 1 (a). C-Team task display screen showing the aircraft (green arrow), airports (green circles with center runway), restricted area (red circle) and the route traversed (red line) to reach the exit B. (b) Accumulated routing paths, representing the task complexity, and the trajectory used by participants for air traffic control.

by the red line. The delay encountered in activating an aircraft upon its appearance on the C-Team display screen is called response time. Routing time, the time taken for the aircraft to reach the exit B, is defined as the amount of time between the appearance of aircraft on the screen and final time to reach the target exit/airport. Figure 1(b) shows the accumulated routing paths of all aircraft from Participant 2, Session 4. These path maps show the complexity in routing introduced by the central restricted area and the changes in aircraft orientation, which are indicated by the accumulated red lines around the airport in all four directions. Upon completion of the task, the performance data were saved to a replay file for further processing during the data analysis procedures.

The experimental protocol had two phases: training and recording. During the training phase, participants were briefed on the use of the MRAB software and performed four MRAB practice sessions on different days within a week. After the MRAB practice sessions, participants underwent three training sessions of C-Team to get them acquainted with the task requirements and to develop their own strategies for controlling aircraft. In the recording phase, participants took part in four sessions, each of which was conducted on different days. Each recording session consisted of initial MRAB test, followed by the C-Team air traffic control task, with simultaneous EEG recording, and final MRAB test. Four C-Team sessions varied by 30 min (30 min, 60 min, 90 min and 120 min).

EEG Data Acquisition

EEG data were collected using a 128-channel, high-density system at a sampling frequency of 250 Hz. During recording sessions, participants were advised to minimize facial movements and eye blinks to reduce artifacts. An impedance check for the electrode cap was performed at 60-minute intervals during sessions 3 and 4 to keep the impedance lower than 50 KΩ to ensure high signal-noise-ratio (SNR) in EEG data. The impedance check lasted for 5 to 10 minutes in all participants.

Performance Data Analysis

The performance data obtained from the C-Team replay files and MRAB log files were backed up after the successful completion of each session. Response times and errors were computed for MRAB tasks that were performed before and after the C-Team task. We statistically compared response times and numbers of errors from pre-task and post-task MRAB tests. To further evaluate the individual cognitive test performance in MRAB, we established a baseline performance, averaged from the MRAB data obtained during three C-Team training sessions, which showed stable performance after the initial eight MRAB practice sessions. We then compared the performance of MRAB tasks from the recording sessions with the established baseline to study the effects of fatigue associated with time on task.

C-Team data were obtained from the replay files to compute performance measures such as response time, routing time, number of crashes, and number of warnings. The crash count was a composite of the number of mid-air collisions, not being lined up with the runway at the time of landing, colliding with boundaries of C-Team airspace, and entering a section of restricted air space. A proximity warning was issued prior to a crash. The C-Team data were segmented into 10-minute intervals, and average values of response time and routing time were computed within each interval. Parameters such as crashes and proximity warnings were also computed for the respective segments. A reference segment with the best performance within the first 50 minutes of the session was identified as the baseline segment. Two-tail t-tests, using a significance level of $p < 0.05$ compared to the baseline segment, were then performed to identify the segments showing significant change in response time and routing time for Sessions 3 and 4.

EEG Data Analysis

EEG data were manually inspected for channels with higher voltage fluctuations over the course of recording and were marked as bad channels. EEG data on the marked bad channels were then interpolated from neighboring channels through the bad channel replacement tool in EGI net station 4.2 (Electrical Geodesics, Inc., Eugene, OR). The procedure was reasonable since the electrical field in the neighboring areas usually had continuous distribution due to the volume conductance effect. After bad channel replacement, a band-pass filter of 0.5 - 100 Hz was applied to the data.

The C-Team task required frequent hand movements due to the use of a computer mouse to perform control actions. This was accompanied by frequent head movements, which created artifacts in EEG data (i.e., electromyography, EMG). These artifacts usually showed temporary high-amplitude, high-frequency components, and many EMG signals had localized spatial distributions over the scalp. The artifacted EEG data were identified by visual inspection and removed using the Fieldtrip software (Oostenveld, Maris, & Schoffelen, 2011).

EEG data were then segmented into 10-minute intervals on which further analyses were carried out. To remove the artifacts introduced by the impedance check on Sessions 3 and 4 data, we performed an independent component analysis (ICA) using EEGLAB software (Delorme & Makeig, 2004) on continuous EEG data before segmentation. During this process, the EEG data were applied with an extended infomax ICA, using Runica (Makeig, Jung, Bell, & Sejnowski, 1996) from the EEGLAB toolbox.
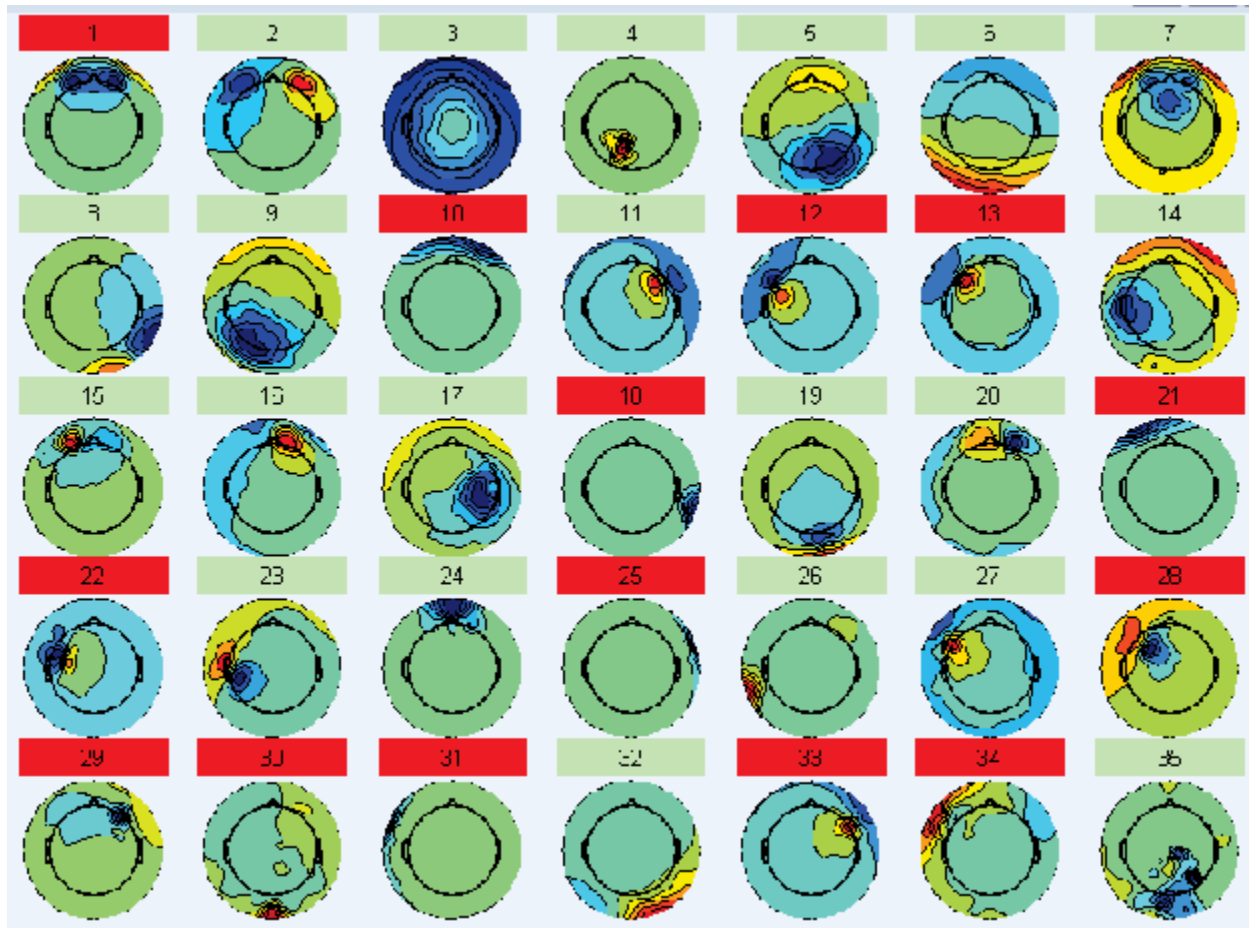
Figure 2 (a). Identified artifact components after running ADJUST artifact rejection method in EEGLAB.

We set the number of independent components (ICs) to 64 and used the ADJUST (Mognon, Jovicich, Bruzzone, & Buiatti, 2010) plugin from EEGLAB tool to remove artifacts related to eye movements and generic discontinuities (Figure 2(a)).
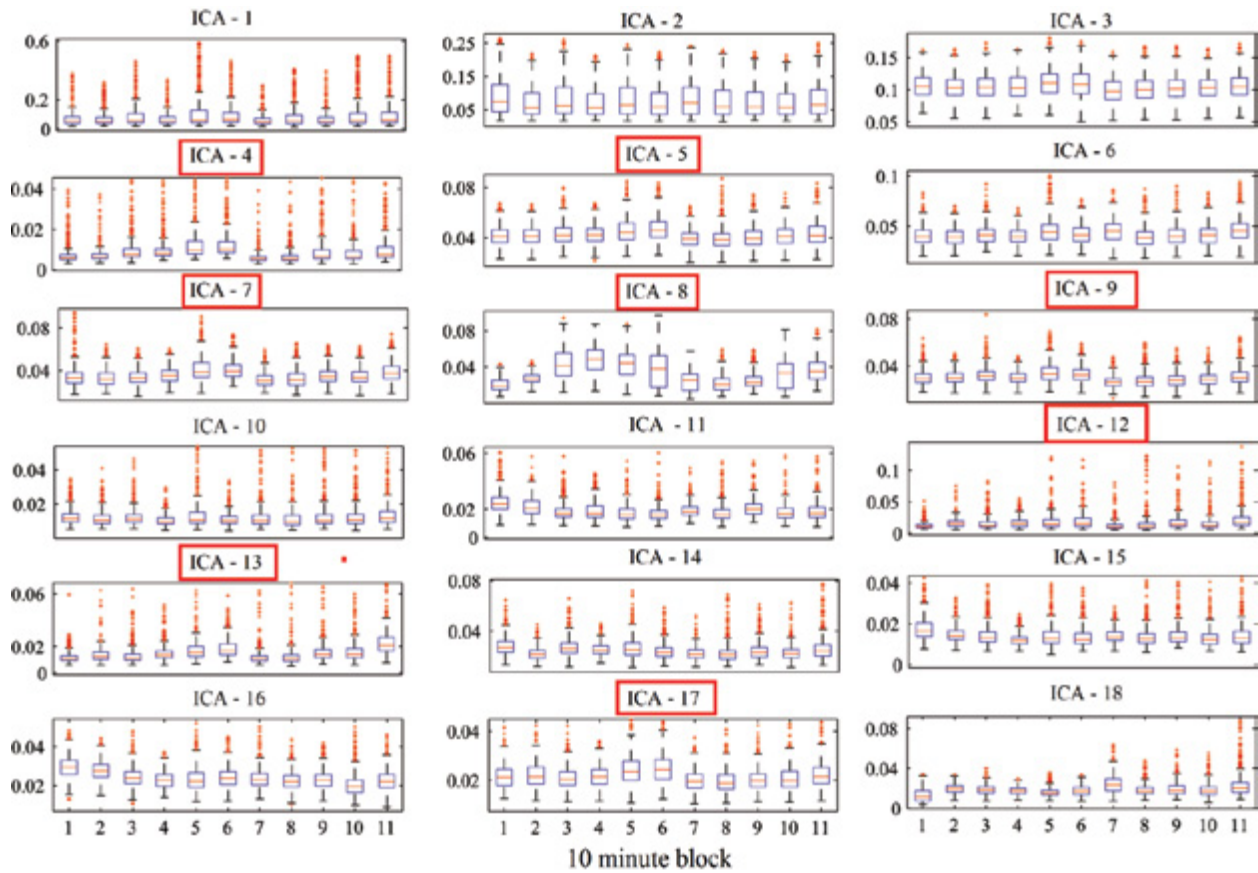
Figure 2 (b). Impedance check induced artifact removal based on the visual inspection of power spectral plots. The components impacted by impedance check that were identified and removed are marked using red boxes.

Components affected by the impedance check were visually identified based on the power spectral density (PSD) of each (in the Whisker plots of data from 10-minute segments), as shown in Figure 2(b). The artifacted components are indicated by red boxes. By removing these artifact ICs, the "artifact-free" EEG data were reconstructed from the residual EEG data.

The above processed data were sectioned into 1-second epochs, and a short-time window Fast Fourier Transform (FFT) was applied with a frequency resolution of 1 Hz to obtain spectral powers of three frequency components, which were theta (4 Hz - 8 Hz), alpha (8 Hz - 12 Hz), and beta (12 Hz - 30 Hz) components (Figure 3). To determine the time frequency representations using FFT, we utilized a multi-taper approach (Percival & Walden, 1993) with fixed window size of 0.25s and 50% overlap. Segments were windowed using a Hanning window (Blackman & Tukey, 1959), and power spectra were computed and averaged over the resulting eight equal segments in 1 second.

Non-Parametric Statistical Analysis

To identify significant changes in mental state due to time on task, a non-parametric statistical method (Maris & Oostenveld, 2007) was used. This method combines the merits of statistical testing and non-parametric techniques to handle the multiple comparison problems in EEG data. In this analysis, we statisti-

cally compared the first 10-minute segment with the remaining 10-minute segments over time. The comparison study resulted in a sequence of maps that illustrated the EEG spectral power changes as a function of time. The *t*-statistic value for each comparison was computed and the threshold was set at an alpha value of 0.05. *T*-values from all EEG channels were grouped into clusters based on the spatial adjacency of electrodes. The cluster-level test statistic was computed as the sum of *t*-values from a cluster. Then we used the non-parametric method to find the significant clusters using a permutation procedure. The procedure involved combining data from two 10-minute segments (which are compared) into a single dataset and then randomly drawing samples from the combined dataset to form two new groups of data of the original size. This procedure is known as random partitioning. The cluster-level test statistic was then computed for these two randomized partitions in the same manner as for the original 10-minute segment data. Repeating this random partitioning an infinite number of times results in a permutation distribution in which the *p*-value is called the permutation *p*-value. Due to practical constraints, the permutation *p*-value was obtained using a Monte Carlo estimate, which was obtained by repeating the random partitioning a large number of times (e.g., 1,000). A permutation *p*-value was obtained that was the proportion of a random partition that had an observed cluster-level test statistic
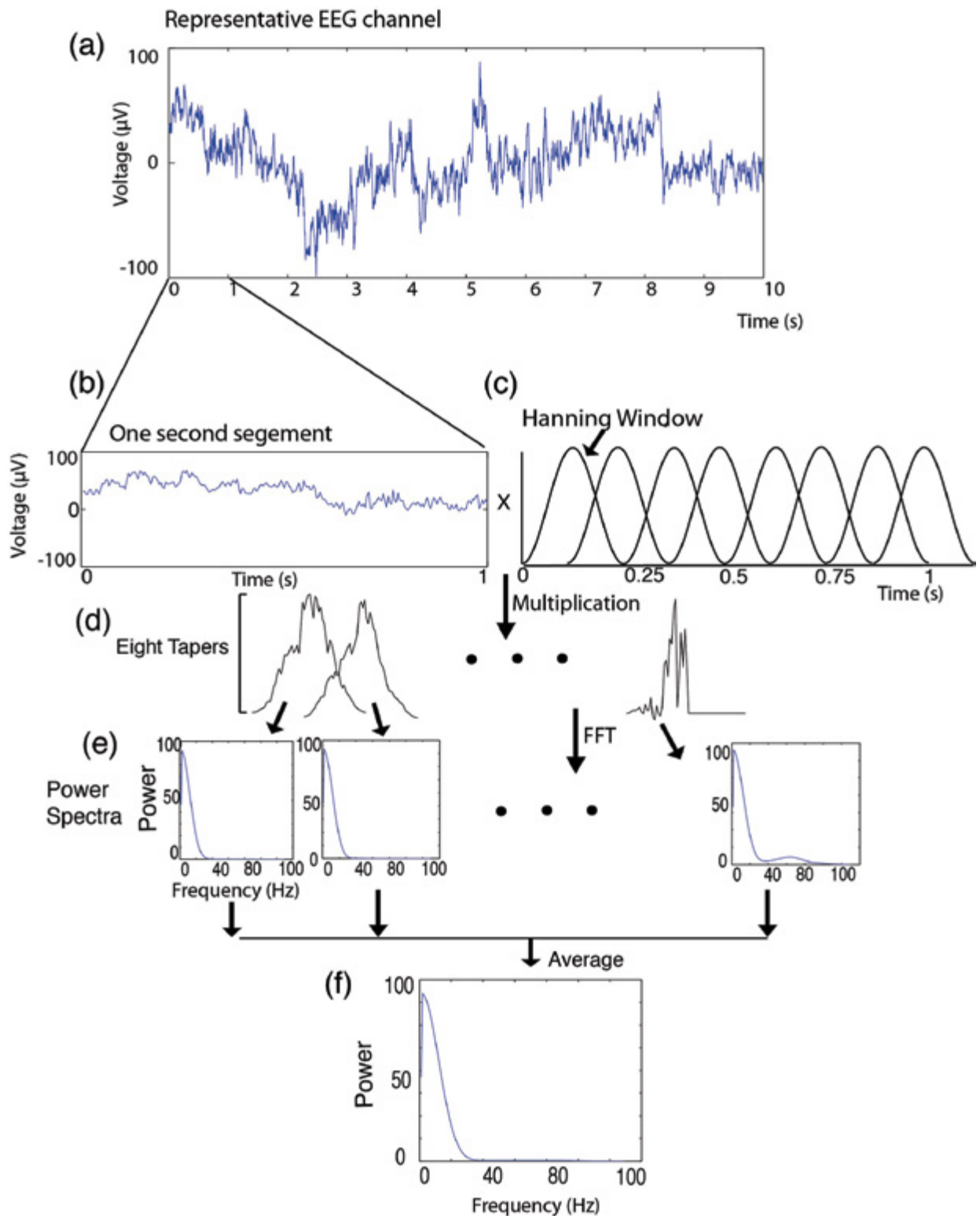
Figure 3. Computation of EEG PSD. (a) 10-second EEG signals from one channel from recordings; (b) EEG signals in a resolution of one second used to perform the FFT calculation; (c) One-second EEG signals multiplied by a sequence of Hanning windows each of 0.25-second length and 50% overlap; (d) Resulted eight periodic tapers from the operation of Hanning. windows; (e) PSD from each taper; (f) EEG PSD obtained by averaging PSDs from eight tapers.

greater than the cluster-level test statistic from original segment data. If this *p*-value was less than the set critical alpha value (< 0.05), we concluded that the two 10-minute segments were significantly different.

The above-mentioned non-parametric statistical method was implemented in the Fieldtrip software (Maris & Oostenveld, 2007), and its graphic illustration is displayed in Figure 4. A *t*-statistic was then plotted out at each electrode indicated by three shades of colors to illustrate the change in power spectra over human heads as a function of time. A blue color represented a significant increase, while a red color indicated a significant decrease. A green color indicated no change in the power spectra compared to the first 10-minute segmented data (see Fig. 4 for examples). The significant change in EEG spectral powers, identified by the implementation of the statistical test, indicated a possible mental state transition, as discussed below.

Mental State Analysis

Mental state was determined based on the activation of the neural networks, which were responsible for the neural computation performed by the human brain. For example, mental states have been studied as microstate and transition between different microstates as an indicator of a functional status change in the human brain (Pascual-Marqui, Michel, & Lehmann, 1995). Such transitions of mental states, or microstates, are reflected in rhythmic EEG signals. In other words, EEG measures the signal produced by the synchronous discharging population of cortical neurons, which are shifted under different mental states.

To determine the change in brain activity, we selected the channels corresponding to the significant change from non-parametric analyses and searched for the change in the absolute spectral power over time in a specific frequency band (i.e., the theta, alpha, and beta bands). Specifically, the pattern in the median of EEG spectral powers from 10-minute segment data along the time axis (i.e., 0.5, 1, 1.5, or 2 hours) was assessed. This indicated the mean level of activity at each frequency band. We then searched for pattern shifts in the curves for medians as indicators of the mental state transition, as studied by Pascual-Marqui et al., 1995. We hypothesized that the prominent shift in EEG spectral power data was correlated to the time-on-task effect. We
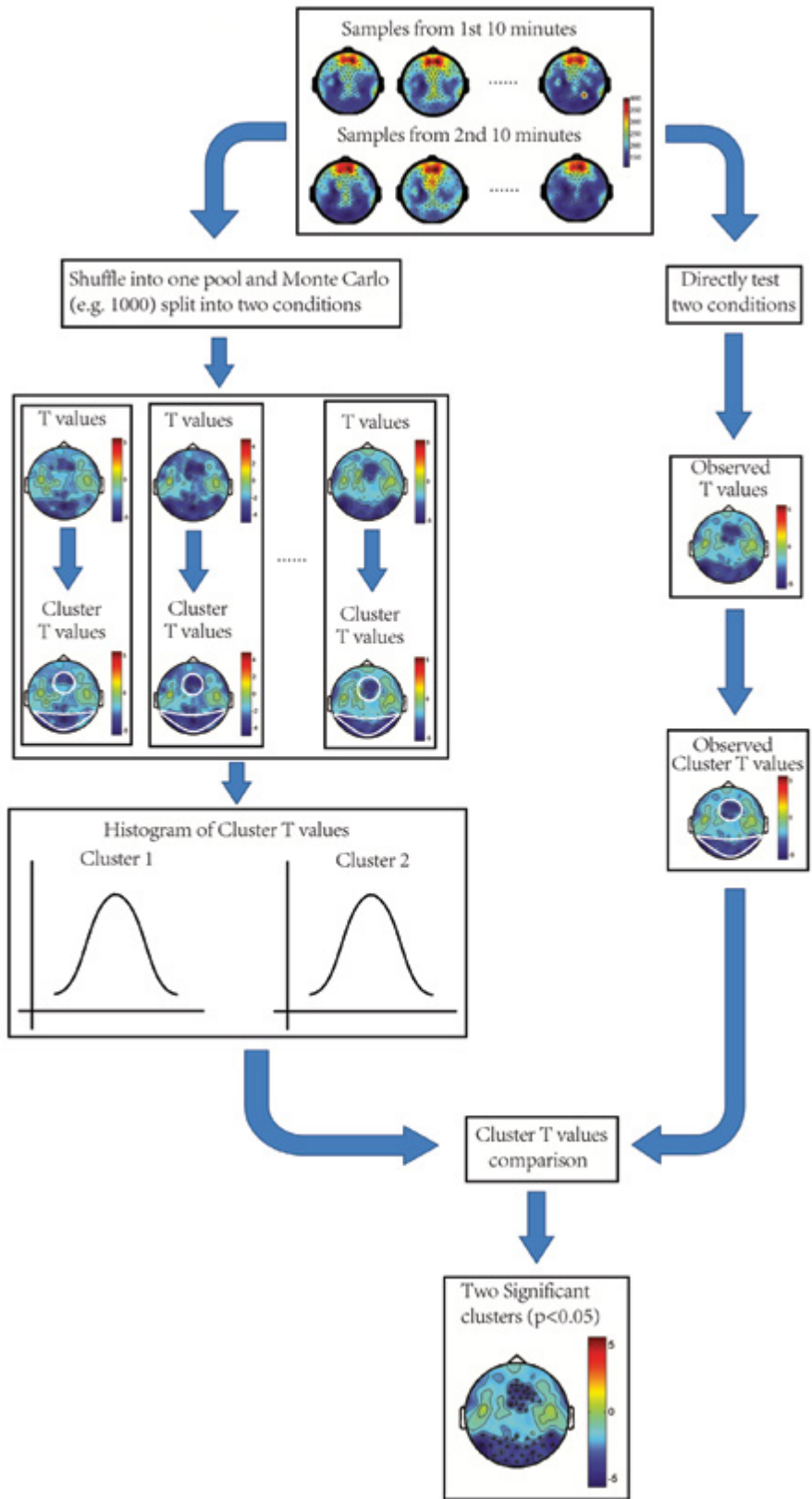

Figure 4. Illustration of cluster-based permutation test for spectral powers on channels between two 10-minute EEG data.

also evaluated these features using other types of data, such as the performance data (see the section below). The time exhibiting the significant prominent shift was noted as the transition time (TT).

Correlation Analysis

To find the association between the EEG patterns indicative of mental fatigue and cognitive performance, we compared performance measures such as response time and routing time with EEG spectral power data over time. Response time and routing time represented the change in performance, while EEG spectral power represented the change in mental state due to the time-on-task effect. We compared the results obtained from non-parametric statistical testing to identify the change in spatio-temporal patterns of EEG spectral powers and changes in C-Team performance measures over time.

RESULTS

MRAB Results

Overall results from the MRAB tasks showed stable performance with no significant changes in reaction time both before and after sessions of any length (i.e., 0.5, 1, 1.5, and 2 hours). The comparison study against baseline performance using *t*-tests showed similar performance between pre-task and post-task tests, with the exception that there were observed differences for the Vigilance and Filtering tasks. However, these differences between pre-task and post-task were not consistent among participants at the level of group analysis. Hence, no conclusive evidence of time-on-task effects was indicated by the performance data from the MRAB tasks. Meanwhile, the performance measures obtained from C-Team showed significant effects of time on task, as discussed below.

C-Team Results

C-Team performance data were used to evaluate the time-on-task effects during the task scenarios. In general, when time on task became longer, all participants had increased response times in activating aircraft and increased routing times to reach destinations. It appeared that it took about 20 to 30 minutes for participants to reach stable performance after beginning the task. This result was also suggested by the EEG data and will be discussed in the next section.
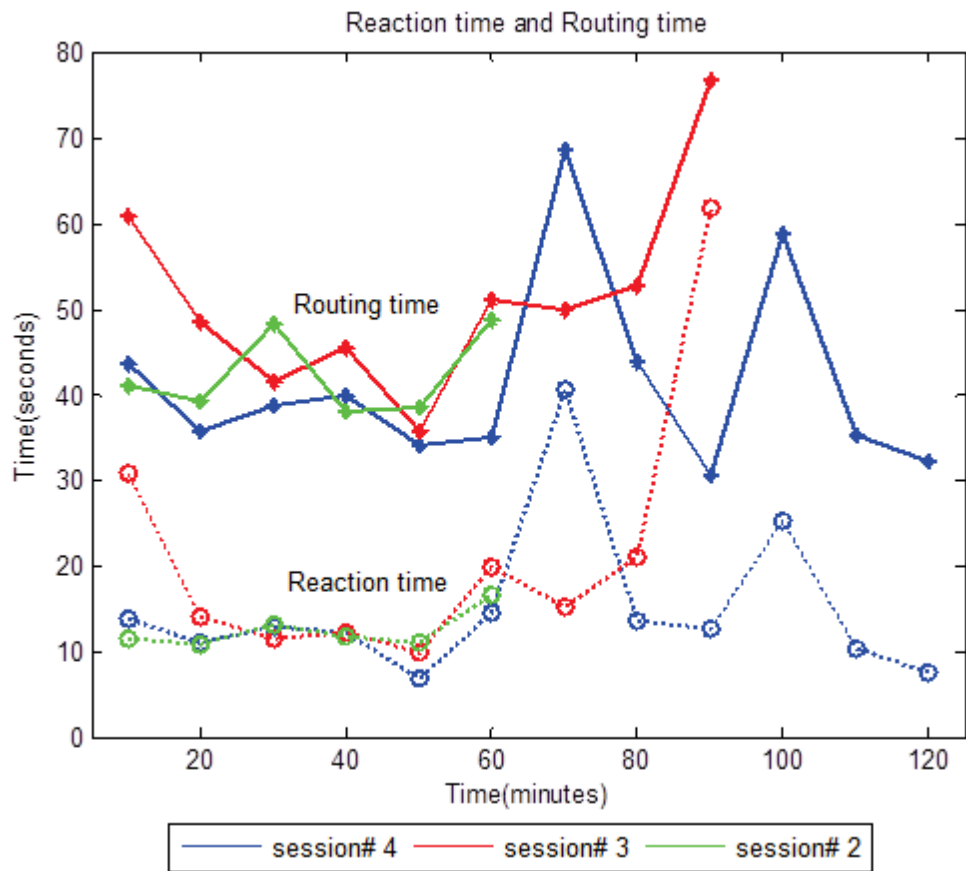
Figure 5 C. Team performance measures, reaction time, and routing time are plotted over time to show the significantly deteriorating performance happening around 60 - 80 minutes for session 2 (blue), session 3 (red), and session 4 (green) from participant 3.

Figure 5 shows the response times and routing times from sessions 2, 3, and 4 of Participant 3. During the first 60 minutes, response times and routing times followed a similar pattern for all three sessions. That is, there was an initial drop in times, followed by a gradual increase toward the 60-minute mark. Following the 60-minute mark, significant changes were observed in Sessions 3 and 4 response times and routing times. These changes were evident for all participants.

Table 1. Response time significance level between reference interval (C*) and rest of the time intervals (T#) obtained from C-Team task of all participants (P) for session 4.

		Time Intervals									
		T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
	C*										
P1	T4	-	-	0.372	0.117	0.074	0.131	0.368	0.775	0.108	0.294
P2	T4	-	-	0.320	0.220	*0.009*	0.089	0.385	0.150	0.699	-
P3	T5	-	-	-	*0.023*	*0.000*	*0.011*	0.107	*0.000*	0.107	0.506
P4	T2	0.130	*0.021*	0.486	0.119	*0.016*	0.095	0.079	0.111	*0.023*	0.793
P5	T5	-	-	-	0.065	0.084	*0.000*	0.069	*0.004*	0.861	-
P6	T5	-	-	-	0.161	*0.010*	0.702	*0.009*	0.298	0.154	0.286
P7	T2	0.358	0.217	0.462	0.053	*0.013*	*0.025*	0.634	0.104	0.094	0.696
P8	T2	0.513	0.083	0.632	0.068	0.244	*0.014*	0.261	0.160	0.155	0.502
P9	T4	-	-	0.770	0.291	0.291	0.160	0.536	0.210	0.613	0.003
P10	T2	0.457	0.389	0.445	0.344	0.781	0.415	0.520	0.120	0.509	0.002

Note: The values italicized and underlined are identified to be significantly increasing ones based on the t-test conducted with significance level of $P < 0.05$.

Table 2. Routing time significance level between reference interval (C*) and rest of the time intervals (T#) obtained from C-Team task of all participants (P) for session 4.

		Time Interval									
		T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
	C*										
P1	T4	-	-	0.795	0.183	*0.009*	0.118	0.205	0.466	0.253	0.580
P2	T5	-	-	-	0.591	0.201	0.178	0.861	0.672	0.661	0.260
P3	T5	-	-	-	0.153	*0.000*	0.199	0.222	*0.011*	0.512	0.549
P4	T5	-	-	-	0.578	0.349	0.692	0.429	0.913	0.784	0.080
P5	T5	-	-	-	0.521	0.729	0.054	0.553	0.706	0.601	0.381
P6	T5	-	-	-	0.336	*0.006*	*0.044*	0.084	0.905	0.071	0.798
P7	T5	-	-	-	0.591	0.178	0.135	0.980	0.817	0.323	0.315
P8	T5	-	-	-	0.628	0.433	0.108	0.788	0.466	0.410	0.698
P9	T4	-	-	0.600	0.310	0.450	0.136	0.792	0.610	0.904	0.377
P10	T1	0.270	0.052	*0.008*	*0.013*	0.130	0.093	0.632	0.251	0.726	0.326

Note: the values italicized and underlined are identified to be significantly increasing ones based on the t-test conducted with significance level of $P < 0.05$.

Tables 1 and 2 present the statistical results via comparing 10-minute segment data with the baseline segment data for Sessions 3 and 4, respectively. As shown by the *t*-test results, we inferred that there was a significant increase in response time and routing time that occurred approximately between 60 and 80 minutes. Following the 60-80 minute region, some participants, such as Participant 3, exhibited momentary recovery in terms of performance, followed by a significant decline in performance. It is possible that these participants noticed their performance decline and were able to temporarily return to baseline performance.

Table 3. Summary of C-Team task performance measures for all the sessions.

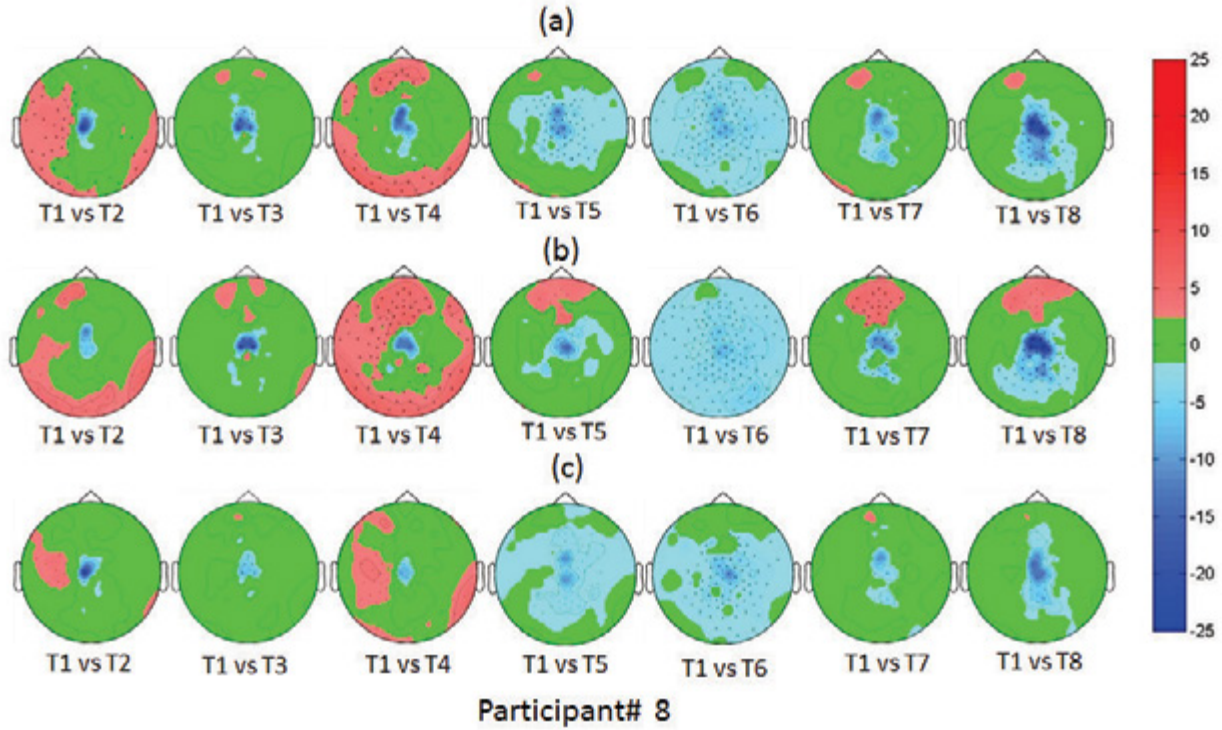| | Mean | | | | |
	Response time	Routing time	Crashes	Warnings	Active plane/second
Session 1	4.26	29.72	1.40	2.00	1.25
Session 2	5.08	31.56	3.67	3.33	1.31
Session 3	5.78	31.23	6.67	9.80	1.24
Session 4	4.91	30.31	4.50	6.80	1.26

Figure 6. Scalp maps plotted out from the non-parametric statistical test results showing significant changes in EEG power spectra across alpha (a), beta (b) and theta (c) over time, comparing the first 10-minute segment with subsequent segments, and resulted significance levels are color coded and displayed. Red indicates a significant decrease, blue indicates a significant increase, and green means no significant change.

Performance decrements were also observed in other measures, e.g., numbers of crashes and proximity warnings, from Session 1 (and 2) and Session 3 (and 4) (Table 3). Both the average number of crashes and proximity warnings were significantly higher in Sessions 3 and 4 than in Sessions 1 and 2, averaged over all participants. This was likely because Sessions 3 and 4 were of longer duration and, hence, participants had more opportunity to experience crashes and proximity warnings. However, it was also interesting to note that the number of crashes and proximity warnings were slightly lower in Session 4, as compared to Session 3. This may have been due to some sort of recovery effect, such as described in the previous paragraph.

EEG Results From Spatial Analysis

To spatially represent the change in power spectra over different segments, we used scalp maps and three shades of colors (Fig. 6). All changes are referenced to the first 10-minute segment. Areas marked in blue indicate a significant increase in EEG power spectra. Areas marked in red show a statistical decrease, and areas marked in green represent no statistically significant change. Notice that the blue areas follow an increasing pattern across time, and thus are thought to represent a time-on-task effect. Areas marked in red do not exhibit a consistent trend across time and, thus, are thought not to be a useful marker for a time-on-task fatigue effect. Because of this, we focus subsequent discussion only on the blue regions.

The results from the non-parametric analysis suggest significant and consistent changes over time in power spectra in theta, alpha, and beta frequency bands, as shown in Figure 6. These power spectral changes were observed by comparing the first 10-minute segment to the subsequent 10-minute segments in sequence, which were localized to frontal midline and parietal areas. Further, to illustrate the consistency of these results across sessions, we have presented the alpha power spectral plots obtained from all four sessions.
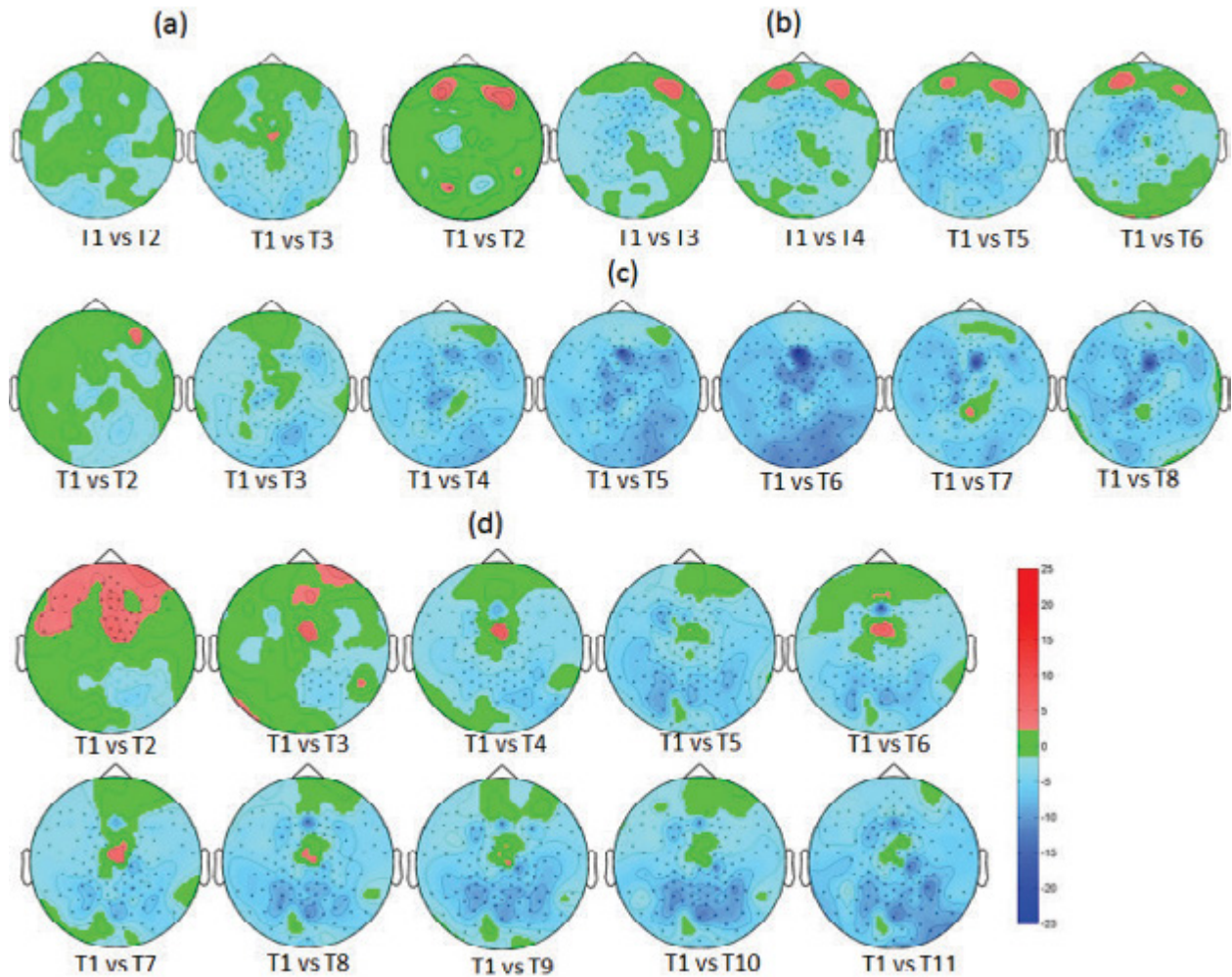
11

Figure 7. Scalp maps plotted out from the non-parametric statistical test results showing significant changes in EEG alpha power spectra over time on obtained from session 1 (a), session 2 (b), session 3 (c), and session 4 (d) comparing the first 10-minute segment with subsequent segments, and resulted significance levels are color coded and displayed. Red indicates a significant decrease, blue indicates a significant increase, and green means no significant change.

Figure 7 shows the scalp maps that indicated a significant change in alpha power spectra across all sessions from Participant 9. A similar pattern was also observed for theta and beta bands that are not shown here. As stated earlier, a significantly increasing pattern in alpha band was observed over time to be localized within the frontal and parietal areas along the midline for Sessions 2, 3, and 4. Session 1 showed random changes similar to those appearing at the beginning of the longer sessions, which are thought to be the result of temporary changes in brain activity not related to the time-on-task effect. Due to this observation, the performance data from Session 1 (the 30-minute activity) was not used to evaluate the time-on-task effect. Instead, performance data from Sessions 2, 3, and 4 were used. Results from the non-parametric analysis for varied session lengths provided more information on increasing patterns of power spectra with time-on-task and identified spatial regions (along the midline from the frontal area to the parietal area over the head) associated with fatigue.
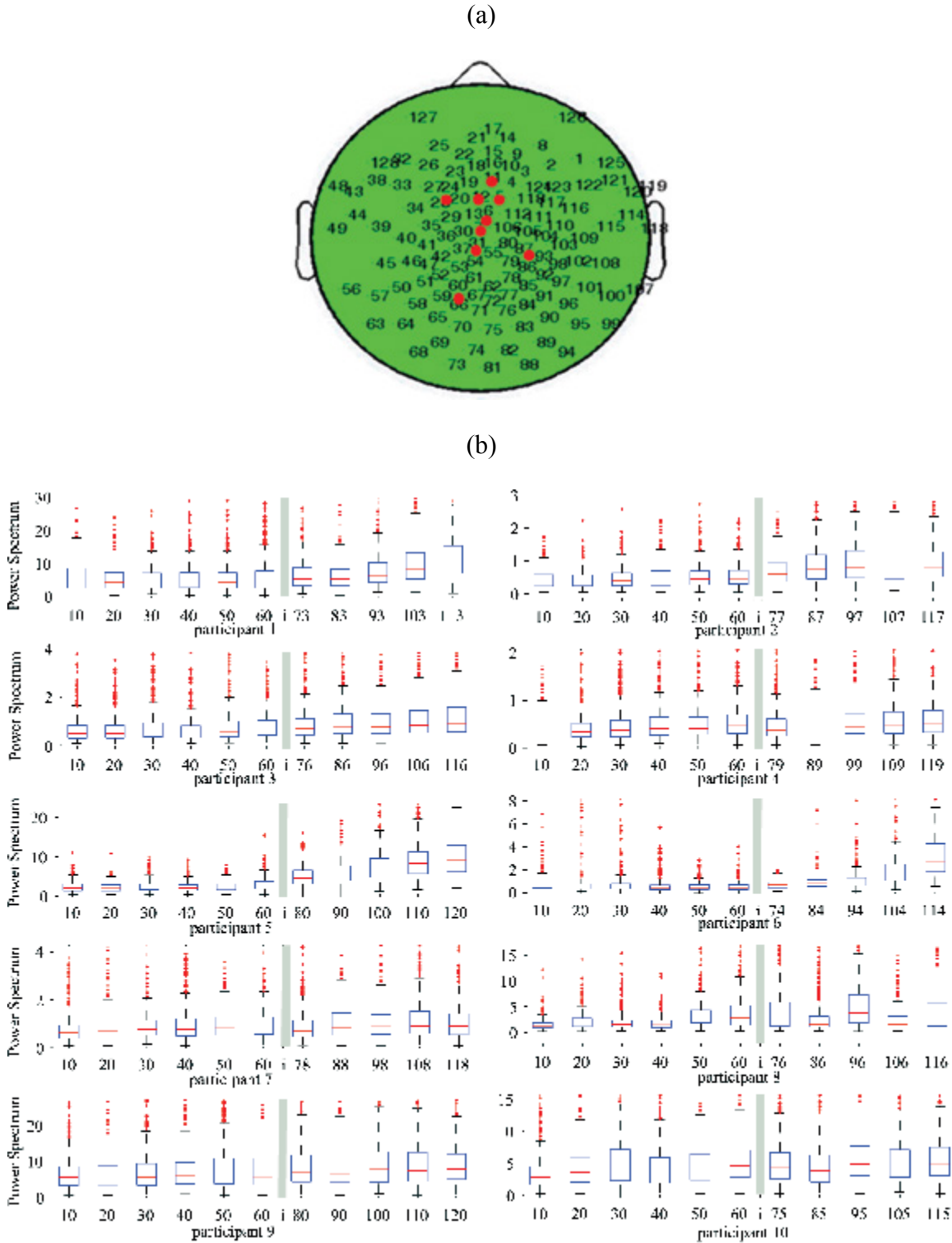
Figure 8 (a). Scalp electrode locations selected as the representative channels used for mental state transition time computation. (b) Whisker plots of EEG alpha power spectra used to identify the transition times of mental states. The grey bars represent the time durations used for impedance check.

Indicators of Mental State Transitions

To determine mental state change, we selected representative channels from the spatial areas that are identified from the non-parametric statistical analysis and increased EEG spectral powers over the alpha band. Figure 8(a) shows the selected representative channels, indicated by red dots over the scalp map, all of which appear on the midline from frontal area to parietal area. Figure 8(b) shows the Whisker plots of absolute power data in a resolution of 10 minutes, obtained from the representative channels of all participants in Session 4. The grey bars after the 60-minute mark represent the impedance check interval, during which no EEG data were obtained. From these Whisker plots, one can infer that there was a steady increase in EEG power spectra with significant
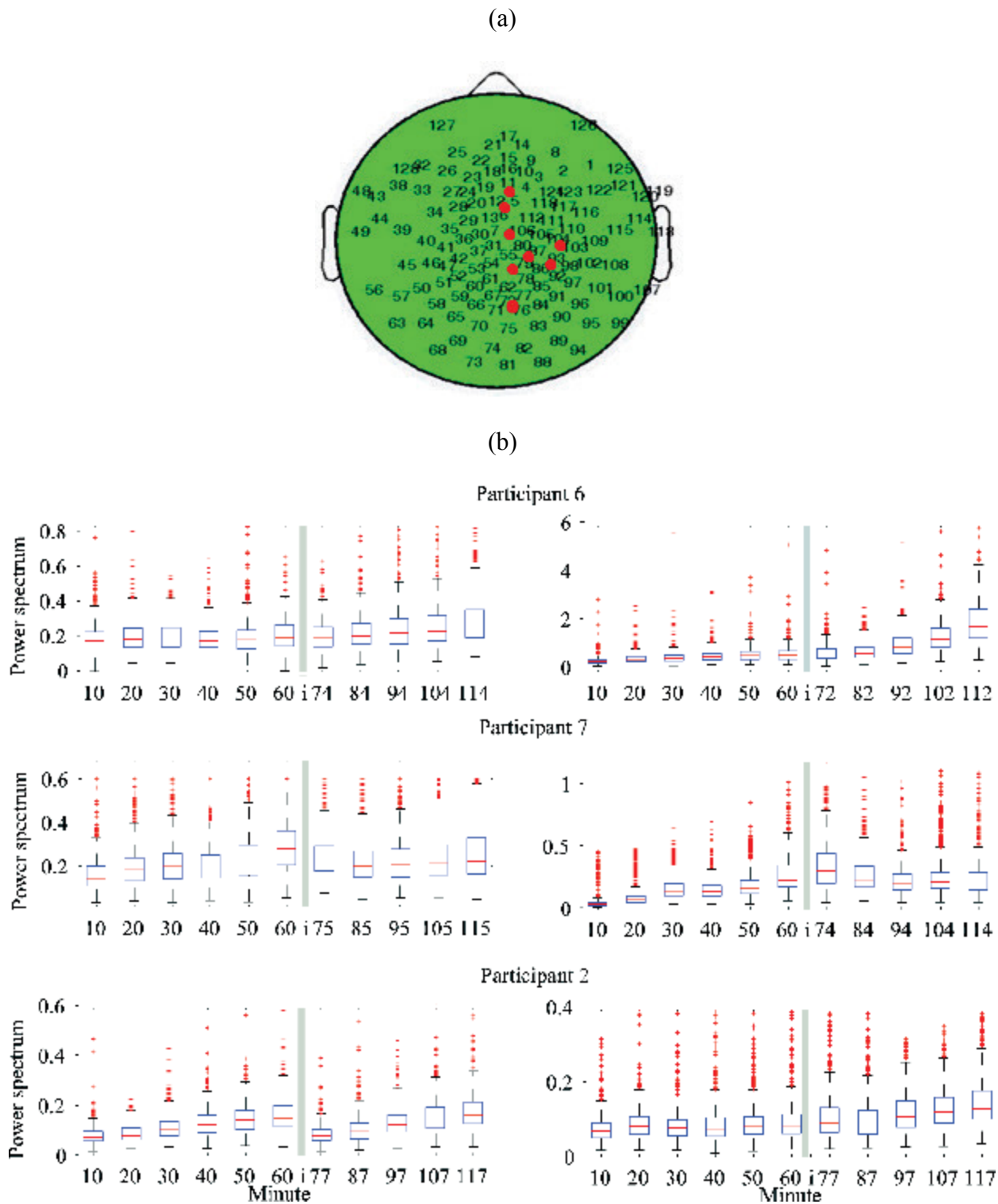
(a)

(b)

Figure 9 (a). Results from our previous study showing the scalp electrode locations for representative channels used indicated by red dots. (b) Whisker plots of EEG alpha power spectra used to identify the transition times of mental states.

changes occurring from 60 to 80 minutes, which varied within different sessions and among participants. In general, most participants showed this increasing pattern in alpha power spectra. However, there were individual variations, such as observed with Participant 8. Despite individual difference in variation, the overall pattern of increasing EEG power spectra and spatial distribution patterns were consistent with the results from our previous study (Dasari, Crowe, Ling, Zhu, & Ding, 2010 Fig. 9), thus suggesting stable results across multiple studies.
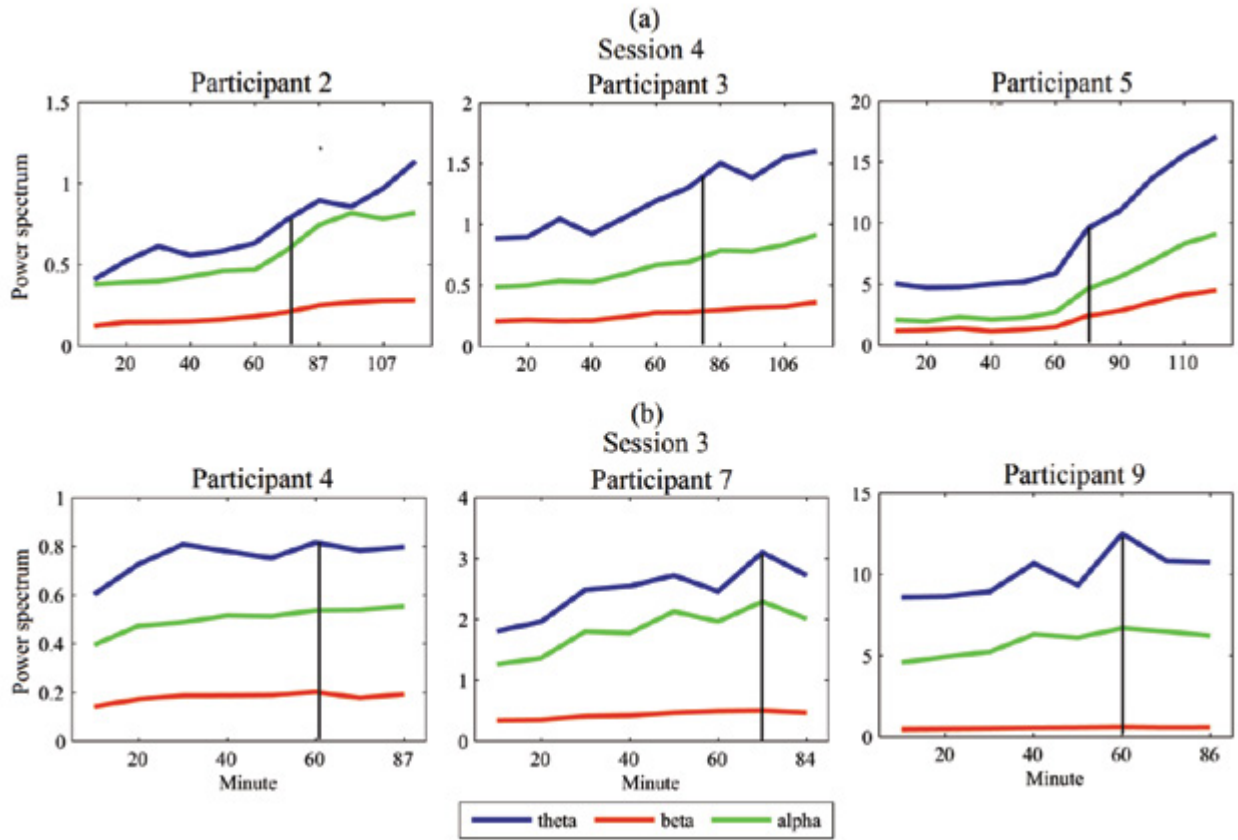
Figure 10 (a). Increasing patterns of median EEG power spectra over time from alpha, beta, and theta bands from session 4 (a) and session 3 (b) data with significant changes occurring around 60 - 80 minutes. Black lines represent the transition time (TT) for mental states.

Figure 10 shows the median values of absolute spectral power data for every 10-minute segment from Sessions 3 and 4. We estimated the transition time (TT), defined as the indicator for mental state shift, as discussed above, using the following procedures. First, from these plots, it can be observed there was a prominent spectral power shift occurring between 50 and 90 minutes in most participants. We broadened this window to be from 40 to 100 minutes and searched for the maximal changes between neighboring segments in this range as TTs, which are marked by the vertical lines in Figure 10 for different participants. This prominent shift in EEG powers was identified and computed as TTs for all participants and sessions (summarized in Table 4). Observe that most transition times are found between 60 to 80 minutes.

Correlation Analysis

The neurophysiological pattern identified in EEG to represent the time-on-task effect (or mental fatigue) depicts a visually observed correlation with cognitive functional decrements observed in C-Team task performance. Fluctuations in performance, represented by response time and routing time, correspond with transition times identified from EEG spectral power data over time.

Table 4. Summary of the mental state transition time identified from EEG spectral power data.

	Participant									
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
	Mental State Transition Time (minutes)									
Session 2	--	60	--	60	60	--	--	--	60	60
Session 3	--	60	75	60	60	--	74	77	60	50
Session 4	73	77	86	60	80	94	60	50	80	60

Note: The blank fields indicate no significant change observed for those participant sessions.
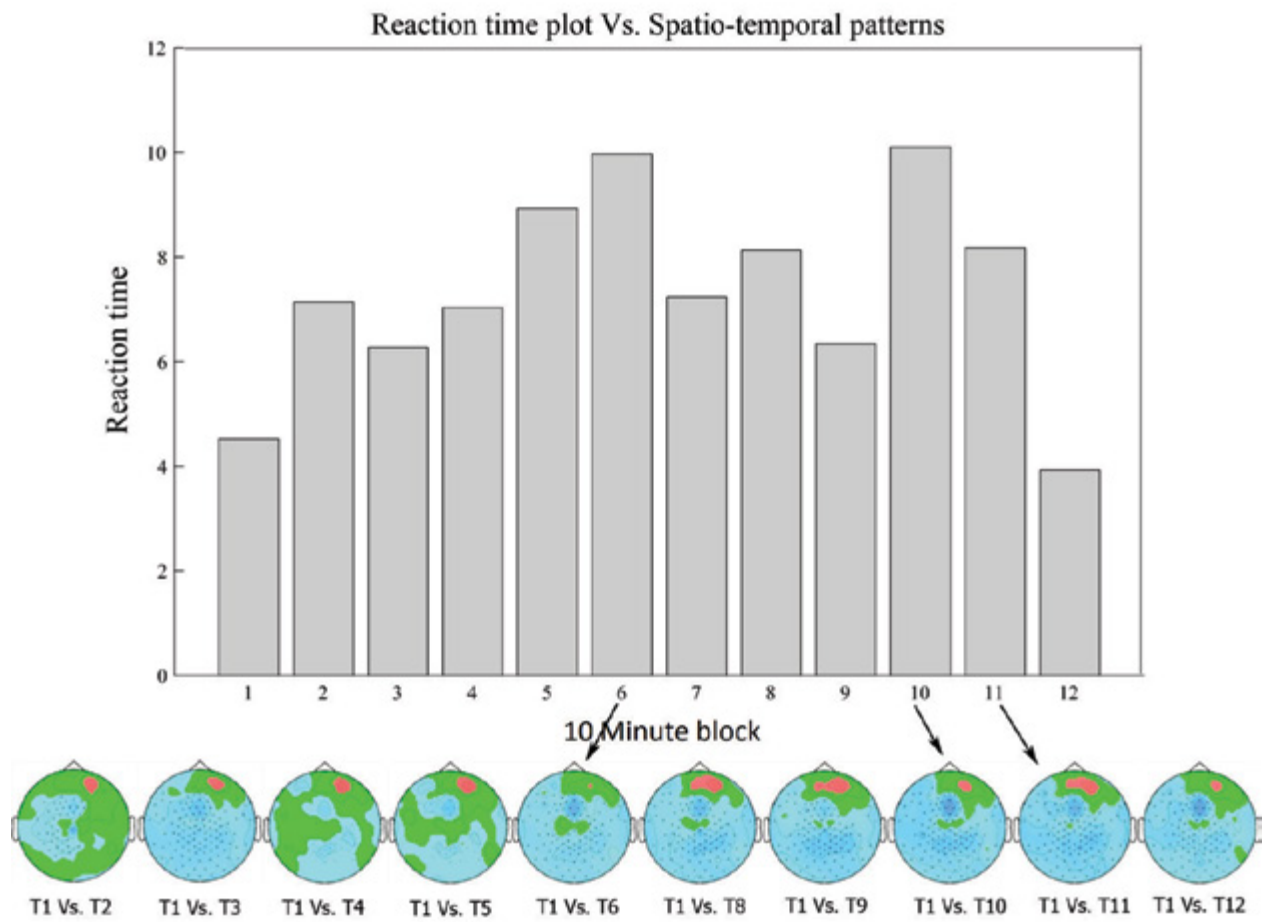
Figure 11. Correlation of reaction times with spatial patterns showing significant changes in EEG alpha power spectra localized to frontal midline region of the brain, from Participant 10, session 4.

Figure 11 shows an example of the visually observed correlation between response time and the spatial maps obtained using the non-parametric method from Participant 10, Session 4. The performance decrements are well-captured by physiological patterns from EEG at both 60 and 100 minutes where the frontal midline region of the brain exhibits increased alpha EEG powers as compared to neighboring segment data (i.e., deep blue color means more changes than light blue color).
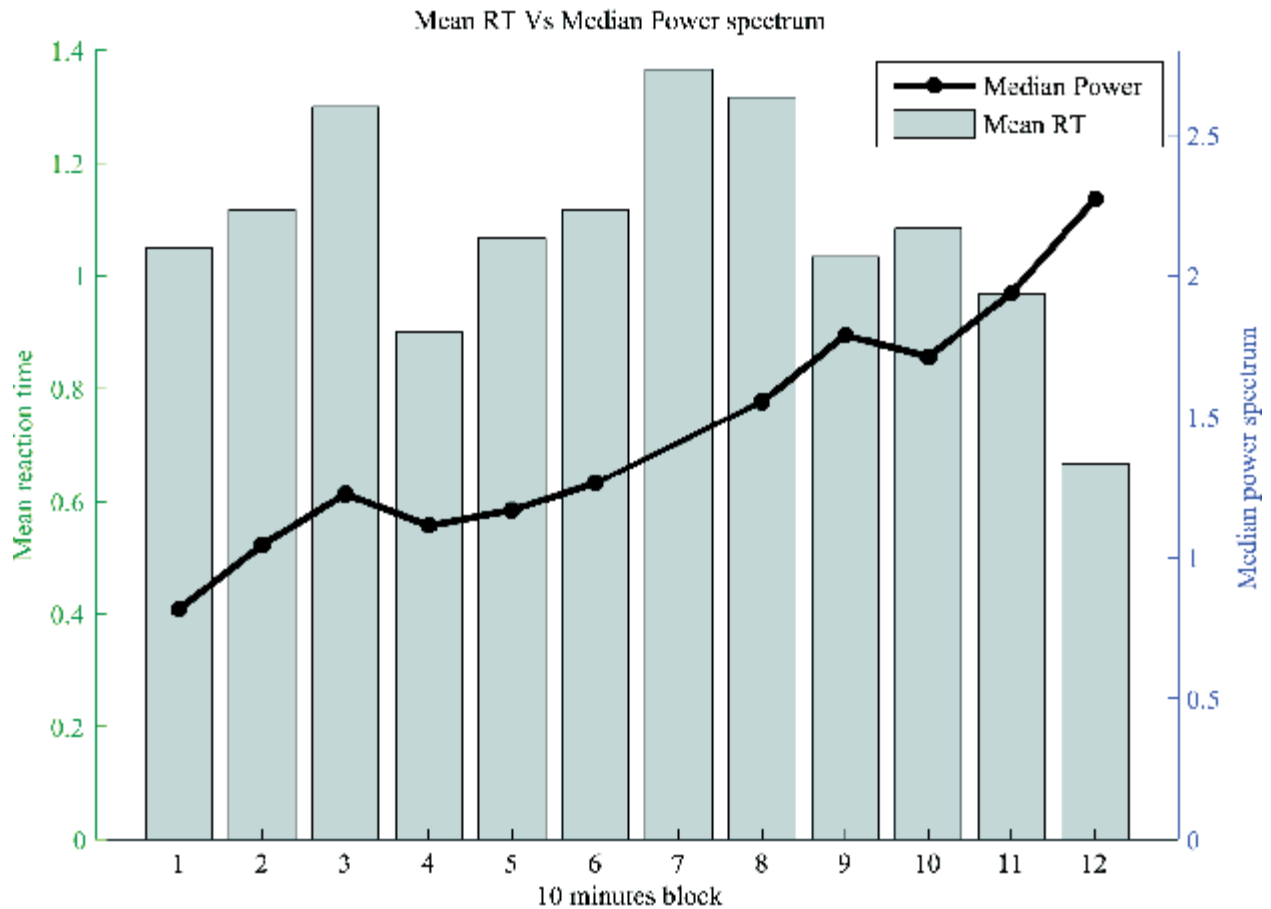
Figure 12. Correlation of alpha median power obtained from EEG power spectral analysis, with reaction time performance over time from Participant 2, Session 4.

Figure 12 shows an example from Participant 2, Session 4, in which the mean response time is shown with the median alpha EEG powers over time. The plots show that slow response times can be visually correlated to increasing patterns of EEG alpha power. The EEG alpha power pattern also follows the response time pattern when fast response times appear at the beginning of the session (due to the alertness) and later in the ninth 10-minute segment (due to the temporary recovery from mental fatigue). The improved response times at the end of session may be attributed to the expectation of finishing the task soon. A similar result is also observed in all participants and sessions. In some participants, such phenomena are also observed to be localized within the parietal region.
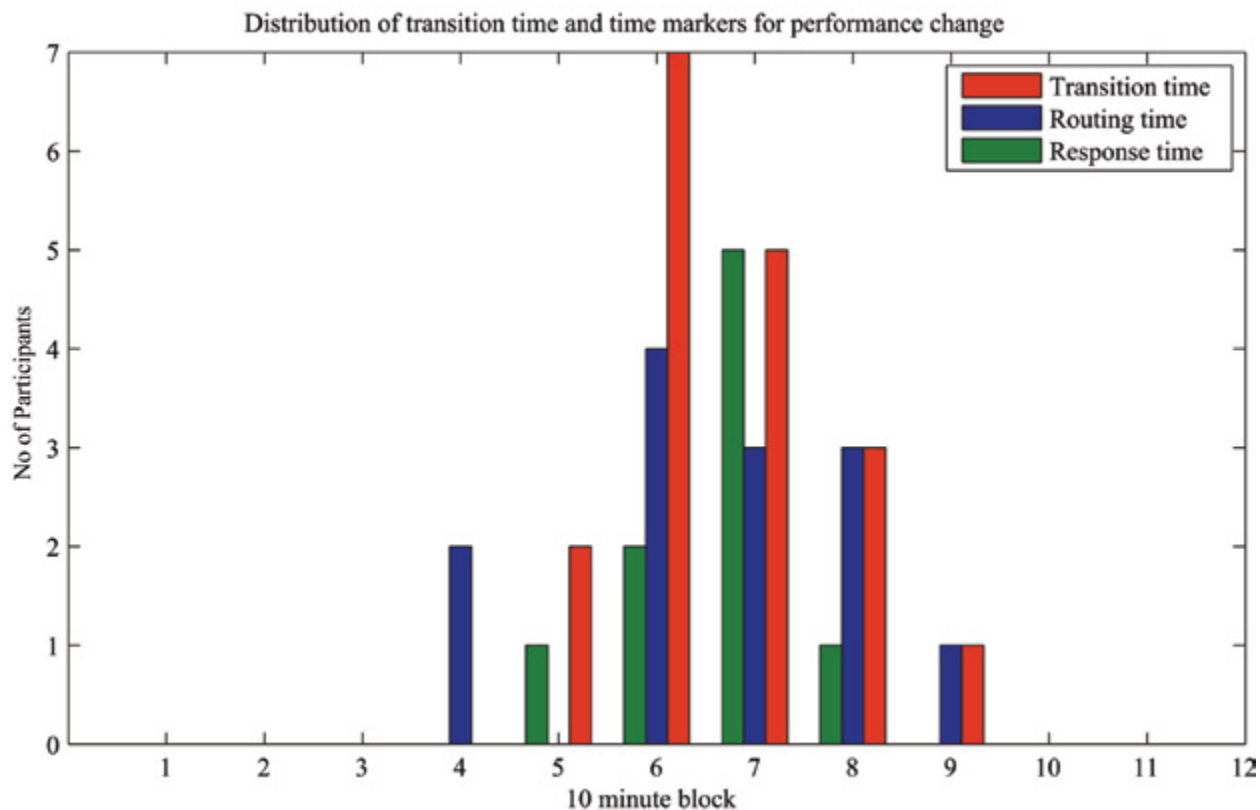
Figure 13. Distributions of number of participants showing significant changes in reaction time (green bar), routing time (blue bar), and mental state transition times (red bar).

For the comparison at the group level, Figure 13 shows the histogram of the number of participants in sessions 3 and/or 4 (combined) that displayed a significant departure from baseline response times and routing times. Also included in the histogram are TTs from all participants. Each bar represents the number of participants falling under the corresponding 10-minute time window, where each red bar represents TT from EEG. Each green bar shows the significant response time change, and each blue bar indicates a significant routing time change. Notice that the histograms for TT, response time, and routing time are mostly clustered in the time window from 50 to 90 minutes and peak between 60 to 70 minutes. Since the time markers for significant changes in response time, routing time, and power spectral changes were mostly found after 60 minutes, data from Sessions 1 and 2 were not considered for this correlation analysis.

DISCUSSION

In this study, we analyzed the association of EEG patterns related to mental fatigue, with deteriorating cognitive performance over time while participants performed a simulated air traffic control task. The low-fidelity air traffic control task used for the present study provided a more realistic approach in assessing performance changes, as the task scenarios mimicked some of the real-world air traffic control tasks. Furthermore, the nature of observations of the time-on-task effect we made in the present study was more spontaneous and realistic, compared to the monotonous single-event tasks used in other

studies (Kramer, Sirevaag, & Huges, 1988; Murata et al., 2005; Trejo & Mullane, 1995).

The realistic nature of the task gives us a better understanding of mental fatigue and its impact on cognitive performance. For instance, response time (i.e., aircraft activation time) in the C-Team task represents the level of alertness in monitoring the appearance of aircraft, while the routing time reflects the planning and decision-making activities necessary for performing air traffic control tasks. Response time and routing time obtained from task performance data in the present study show significant change attributed to the effects of time-on-task fatigue that mostly occurred around 60 to 80 minutes.

EEG spectral power studies show significant alpha and theta activity changes over time that are believed to be associated with cognitive functional changes (i.e., mental state changes). Non-parametric statistical tests implemented on EEG data show that these significant changes are localized to the midline areas from the frontal lobe to the parietal lobe of the brain. The concept of mental state transition was introduced, and the times for such transitions are used to indicate the time markers for the development of mental fatigue, or the time-on-task effect. Obtained transition times from EEG, analyzed by the processes discussed above, indicated prominent changes in EEG data indicative of mental state that occurred approximately around 70 minutes. These patterns were consistent in sessions from the same participants and also consistent from different participants. It is noted that the way to identify transition times study is through the visual inspection of general patterns among all participants,

which was not robust and optimal. More quantitative measures such as medians, changes in medians, variances, and changes in variances of EEG power spectra in a finer resolution (e.g., 5 minutes) can be further explored to develop more robust measures.

Individual and group analyses of mental transition times and performance changes produced meaningful visual correlations. Mental state transition times were well correlated with the slow response times and increased routing times. Such results suggest that patterns obtained from EEG data are reliable indicators for the development of mental fatigue and associated cognitive functional decrements. In many examples, EEG rhythmic powers in alpha bands (also in theta and beta bands) fluctuate with the performance data (Figures 11 and 12), which suggests that EEG rhythmic powers are promising, reliable indicators in real-time monitoring and can even be used to predict human performance.

During our study, we also observed the mental effort deployed by participants to momentarily improve their performance after first experiencing a reduction in performance due to the onset of mental fatigue. Examples for Participant 8 are illustrated in Figures 11 and 12, as well as in Figure 8(a). After the identified mental state transition times, the performance of participants show large fluctuations. The initial recovery in performance during these fluctuations suggests that the individual may be attempting to counteract the mental fatigue effects by increasing mental effort. However, the increase in mental effort appeared to be insufficient to maintain the desired performance level and was followed by a subsequent decline in performance. It is possible that multiple episodes of recovery from mental fatigue may be observed under more taxing conditions from those encountered in the experiment. Even though this is speculation, we are certain that future researchers can take advantage of this work and proceed forward to understand how increases in mental effort made after onset of mental fatigue would affect brain functions and subsequent behavioral performance.

One limitation that we experienced during this study was the impedance check at the 60-minute time mark. We conducted the impedance check to make sure the skin-electrode interface impedance was lower than 50 KΩ in order to maintain a high signal-noise-ratio in recordings. Due to this impedance check, 10 minutes of data were lost at the time (i.e., 60 minutes), which is around the identified moment for the critical development of mental fatigue. Furthermore, the impedance check also impacted the alertness level of participants since they were presented with a new event that was not related to the task, even while instructions had been given to participants to ignore the impedance check. To remove artifacts, a post-recording signal processing technique, i.e., ICA, was used (Makeig et al., 1996). An alternative possible solution to this issue is the use of dry electrodes for long hours of EEG recording (Justin, Jason, James, & Glenn, 2009). Furthermore, the MRAB results in the present study did not show consistent differences among pre-task and post-task cognitive tests, which suggests that MRAB was possibly not sensitive in identifying the time-on-task effect. Other possible reasons for this could have been the short nature of MRAB tasks and the variety of small tasks in MRAB that may help participants become engaged after performing long, monotonous C-Team tasks.

Finally, the present study serves as a template for conducting high-fidelity simulation experiments involving actual air traffic control participants. We demonstrated that mental state transitions related to time on task fatigue could be identified while participants performed low- fidelity aircraft separation tasks involving changes in speed, heading and altitude. The regions of the brain associated with performing these tasks are likely to be the same regions activated during actual air traffic control operations. However, the intensity and duration of mental state transitions are likely to be different. Therefore, before any generalization can be made to the air traffic control population, it will be important to replicate this study under high fidelity air traffic control simulation conditions.

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