Increase in brain effective connectivity in multitasking but not in a high-fatigue state

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***Abstract*—Multitasking has become omnipresent in daily activities, and increased brain connectivity under high workload conditions has been reported. Moreover, the effect of fatigue on neural activity has been shown in participants performing cognitive tasks, but the effect of fatigue on different cognitive workload conditions is unclear. In this study, we investigated the effect of fatigue on changes in effective connectivity (EC) across the brain network under distinctive workload conditions. There were 133 electroencephalography (EEG) datasets collected from sixteen participants over a five-month study in which high-risk, reduced, and normal states of real-world fatigue were identified through a daily sampling system. The participants were required to perform a lane-keeping task (LKT) with/without multimodal dynamic attention-shifting (DAS) tasks. The results show that the EC magnitude is positively correlated with the increased workload in normal and reduced states. However, low EC was discovered in the high-risk state under high workload condition. To the best of our knowledge, this investigation is the first EEG-based longitudinal study of real-world fatigue under multitasking conditions. These results could be beneficial for real-life applications, and adaptive models are essential for monitoring important brain patterns under varying workload demands and fatigue states.**

***Index Terms*—multitasking, real-world fatigue, driving, EEG, longitudinal recording, effective connectivity**

I. Introduction

INDIVIDUALS often handle multiple tasks simultaneously during daily activities. Examples include individuals listening to music while walking or running and students taking notes while listening to a class lecture. Although simultaneously performing multiple tasks is normal in our daily life, it may cause distractions that lead to serious consequences, especially during driving. Distracted driving causes a driver's reaction time to be fifty percent slower than normal [1], and many reasons for distraction or attention switching exist, such as mobile phone calls, texting or listening to the radio while driving [1-3]. The factors that contribute to a driver's impaired attention are related to a driver's mental status [1] and the surrounding environment [3-5].

Driver fatigue is one of the factors that should be considered when analysing vehicle crashes [6]. Fatigue may lead to torpid reactions to the surrounding environment, such as steering the car or hitting the brakes. Across previous studies, fatigue was estimated to be responsible for between 10 and 20 percent of vehicle crashes reported in the US in 2016 [7] and led to 21 percent of all fatal crashes and 13 percent of severe injuries between 2009 and 2013 [8]. Therefore, there is a need to

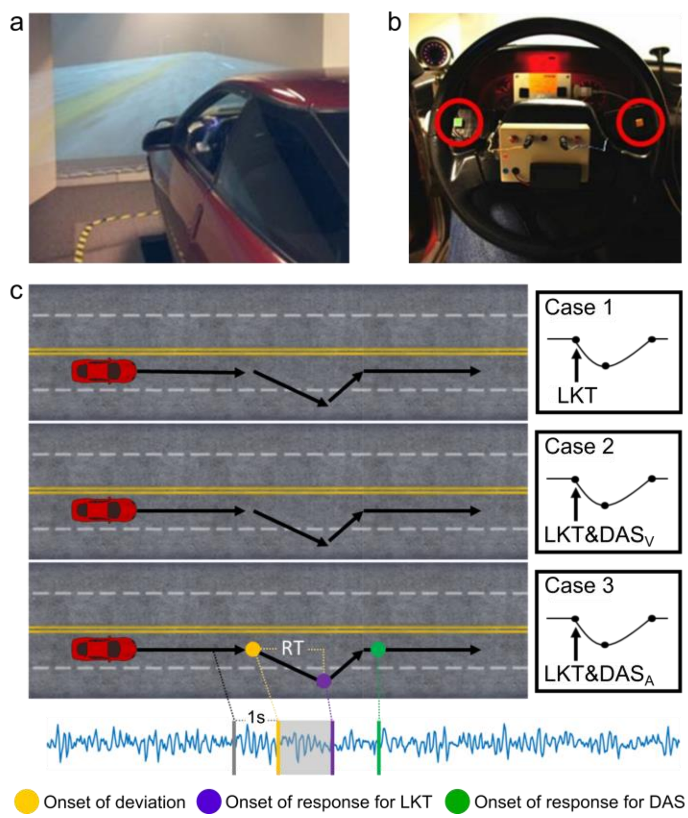

Fig. 1. Experimental design. (a) Virtually simulated environment for the driving task. (b) Two buttons were placed on the wheel for the dynamic attention shift (DAS) task response. (c) Experimental design; case 1: Lane-keeping task (LKT) only; case 2: concurrent LKT and visual DAS (DAS$_V$) dual tasks; case 3: concurrent LKT and auditory DAS (DAS$_A$) dual tasks.

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regulate drivers to avoid using distracting devices, such as cell phones, while driving. Furthermore, understanding the mechanism of driver performance could help to avoid potential accidents on the road.

Cognitive states are believed to be associated with behavioural performance [9, 10]. In addition, neurophysiology is a valid approach for exploring cognitive states [11-15], and many studies have explored the link between fatigue and electroencephalography (EEG) power spectra [16-23]. Researchers have reported that the powers of the theta (4-7 Hz) and alpha (8-12 Hz) bands concurrently increase in bilateral occipital brain regions [24]. An online, closed-loop system was developed to monitor user alertness and improve user responses during driving based on EEG power spectra [25, 26].

Furthermore, there has been increasing interest in neuroimaging research regarding brain connectivity [27, 28], which can be classified into three main types [29]: structural connectivity (SC), functional connectivity (FC) and effective connectivity (EC). SC reflects the anatomical networks, FC is associated with the correlations among brain regions while the brain is processing information, and EC involves the causal dependencies among brain regions. FC uses an undirected graph that can describe the statistical associations among regions; however, EC uses a directed graph that illustrates the causal relationships among regions. Hence, an EC study can provide information about how the information flow is exchanged among brain regions. Therefore, EC results can be used to interpret how information is exchanged among brain areas in a task-related period. Many studies have shown increased across-network FC while performing cognitive tasks [30], including visual attention [31, 32], working memory (2-back task) [33] and movie watching [34] tasks. Studies have indicated that connectivity is correlated with the task load. As the load increases, more brain regions are activated to communicate, exchange information and process external environmental stimuli, and the across-network brain connectivity may therefore increase. However, notably, FC has also been reported to decrease across the brain network during semantic similarity tasks [35] and movie watching [34].

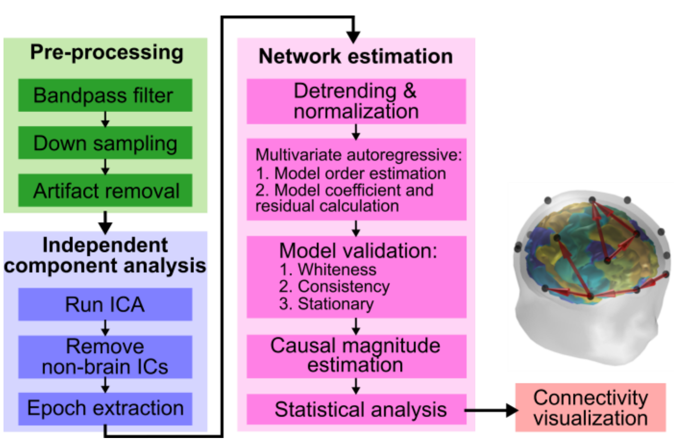

Fig. 2. Flow chart of EEG analysis. The green blocks indicate pre-processing steps at the channel level, the blue blocks indicate source processing steps, and the orange blocks indicate effective brain connectivity estimation steps.

Although previous studies have provided insights into complex brain networks that are correlated with task costs, whether fatigue state variability during the performance of a task is related to fluctuations in brain network organization remains unknown. Fonseca, *et al.* [36] showed evidence of the relationship between sleep-related fatigue and EC in a simulated driving experiment. Borragán, *et al.* [9] showed that prefrontal connectivity decreased with participants' fatigue levels, which were defined by sleep deprivation. In addition, considering time-on-task as fatigue, Huang, *et al.* [37] showed evidence of compensation between cortico-cortical EC and driving performance, ranging from alertness to an intermediate level of vigilance. Furthermore, this compensation seemed to decline from an intermediate to drowsy level of vigilance [37]. However, the changes in brain connectivity remained unclear considering both factors, multitasking, and real-world fatigue. In previous studies [9], fatigue levels have been monitored by sleep deprivation, which is not sufficiently natural. Although several studies have identified evidence of the fatigue state and multitasking factors influencing brain connectivity, there is still limited information on the effects of both factors on brain neural networks during cognitive tasks. In this study, we used a state-of-the-art biomathematical fatigue model called Sleep, Activity, Fatigue, and Task Effectiveness (SAFTE) to assess fatigue levels. Notably, longitudinal recording can benefit from tracking personal real-world fatigue for further applications, such as behaviour prediction or task assignment. To do so, we investigated the ECs of network patterns under different task load conditions and dynamic fatigue states. The fatigue state was measured based on a biomathematical fatigue model [38]. We hypothesized that the EC in high-attention load conditions (concurrent dual tasks) enhances brain network activation compared to that induced under low-attention load conditions (e.g., a single task). Furthermore, we hypothesized that EC varies under different fatigue states for each task condition.

II. Related Work

Brain connectivity has been extensively investigated under altered task load conditions, revealing increasing brain connectivity with the level of the task load demand [30-34]. Furthermore, results have shown that brain connectivity can be physiologically modulated, including by anaesthesia, fatigue, and ageing [39]. For instance, a study based on resting-state fMRI demonstrated a significantly decreased interhemispheric correlation in the motor cortices after a muscle fatigue task [40]. Studies on simulated driving scenarios have shown a clear relationship between connectivity among brain areas and fatigue related to prolonged driving [41, 42]. Al-Shargie, *et al.* [42] revealed that the brain connectivity network is negatively correlated with increasing fatigue level, defined as prolonged time-on-task driving. Furthermore, another study of simulated driving scenarios using effective brain connectivity highlighted the relationship between driving performance and effective connectivity, suggesting that EC patterns are affected by distinctive sleep-related fatigue [36]. Moreover, impairments in prefrontal cortical connectivity led to decreased attention in cognitive fatigue, which was defined as sleep-related fatigue [9].

Nevertheless, research has generally focused on the effects of brain connectivity on task load conditions or the fatigue status rather than considering both factors together. There is still limited information about the effect of sleep-related fatigue on brain connectivity under different workload conditions. In this study, we investigated brain connectivity under different task load conditions in various fatigue states. We hypothesized that brain connectivity is positively correlated with the task load demand; however, this correlation is dependent on the fatigue state of participants.

III. Materials and Methods

This study took a five-month period – one semester – to collect all the datasets. Prior to the start of the main experiment, the recruited participants were given and agreed with the guidelines of the experimental protocol. There were nine data collections for each participant with varied fatigue status, which was monitored with a Readiband device (Fatigue Science Readiband, Vancouver, BC; http://www.fatiguescience.com/). The experimenter called participants to join the experiment on the morning of the day if their fatigue status was suitable for the expected fatigue group. Each participant needed to wear the Readiband device during the entire experimental period (five months). The experimental design was based on a simulated driving scenario [43-46] with three distinctive task conditions to induce different task load levels.

A. Participants

Data were recorded from 16 participants (aged 22.7±1.6 years). All participants had normal or corrected-to-normal vision, and no participants took medications known to affect cognitive functions or had a history of alcohol or drug abuse. All participants were students at National Chiao Tung University (NCTU) in Taiwan who voluntarily participated in this study and provided informed consent. All the components of this study were approved by the Institutional Review Board of NCTU and performed according to the Declaration of Helsinki. The participants received monetary compensation for their participation.

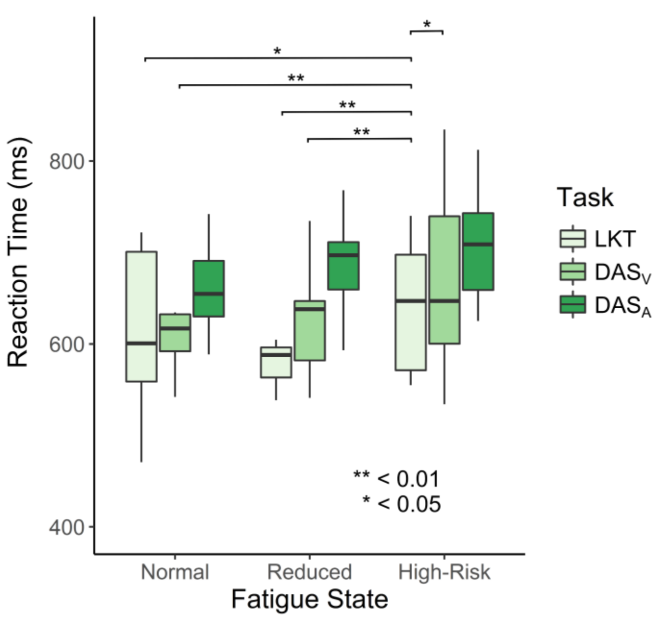

Fig. 3. Reaction time and effectiveness score. Reaction time of lane-keeping task (LKT) across three tasks (LKT, DAS$_V$, DAS$_A$) in three fatigue groups (Normal, Reduced, High-risk).

B. Fatigue state

We applied a biomathematical fatigue model (SAFTE) to estimate the participants' fatigue states in real time [38]. Notably, the SAFTE model was built based on the work/sleep patterns of participants to predict cognitive performance. In addition, the SAFTE model records data on circadian rhythm, homeostatic drive, and sleep inertia, thus characterizing the sleep-wake histories of the participants to evaluate their fatigue state. SAFTE results have been validated as neurobehavioural performance predictors in both experimental and real-life environments [38, 47, 48]. In this study, the fatigue state was measured by the Readiband device, which employs the SAFTE model to estimate fatigue based on psychology. The effectiveness score (ES) is an automatically continuous output from the Readiband device based on the data collected over the previous three days. Each day, the ES index value (range from 0-100) was sent to a server cloud, and the experimenter decided whether the participant was in a suitable state to record the data. The participant had to come to the laboratory within 10 hours after receiving the phone call from the experimenter to collect the data. Therefore, in principle, the participant wore the Readiband every day within the experimental period. The new ES was checked again before the participants performed the experiment. The fatigue level of each participant was classified based on the new ES score for analysis in this study.

C. Experimental paradigm

This study adopted the event-related lane-departure paradigm in a realistic driving simulator environment [43-46] to assess EC under the dual-task condition at varying fatigue states.

Two tasks, a lane-keeping task (LKT) and a dynamic attention shift (DAS) task, were designed in the experimental protocol of this study. The LKT simulated a participant driving a car on a 4-lane road (two lanes in each direction with constant speed at 100 km/h) at night without other traffic, as shown in ***Fig. 1a***. Throughout the entire experiment, the participants were required to maintain travel in the third lane, as shown in ***Fig. 1c***. The car randomly drifted to the left or right in equal proportions. At the time of the onset of deviation, the participants were instructed to control the steering wheel to move the car back into the third lane as quickly as possible. The period from the deviation onset to the time point of turning the steering wheel was defined as the driving reaction time (RT, in milliseconds).

Drivers may sense stimuli that are not directly associated with driving. Two modalities of the DAS tasks, including visual and auditory stimuli, were introduced to manipulate the attention level of drivers. Moreover, the tasks were designed to be as simple as possible to ensure noise-free brain dynamics. In the DAS task, each participant was required to respond to a target, an animal name, and ignore the nontargets by pressing the left or right buttons, which were mounted on the steering wheel (***Fig. 1b***). A target appeared in the form of written (visual) red letters on the screen or spoken words (auditory). The participants were involved in three task cases based on the LKT and DAS task combinations. The first case was LKT only (single task), the second case was concurrent LKT and visual DAS (DAS_V) dual tasks, and the third case was concurrent LKT and auditory DAS (DAS_A) dual tasks in a random order (***Fig. 1***). While the target was displayed on the screen, the time from the target onset to the time of button pressing was defined as the DAS RT.

The Institutional Review Board of NCTU (Taiwan) approved this study. All participants underwent an orientation session that described the experimental procedures and the participant responsibilities during the long-term study; they were informed of the experimental materials, features, and processes and were required to read and sign a consent form prior to the experiments.

D. Data acquisition

All participants ideally performed this experiment nine times; however, participant S06 participated five times; S08 participated six times; S14 participated six times; and S16 participated eight times. In total, 133 datasets were collected over six months. Each experimental session lasted approximately 2 hours (including experimental setup), and the sessions were conducted at roughly two-week intervals for each participant.

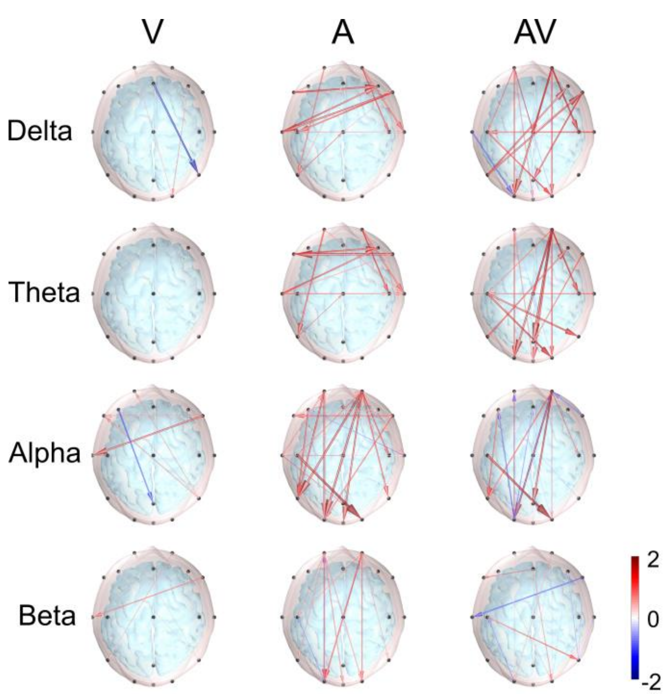

Fig. 4. Topographical comparison of significant EEG effective connectivity differences (p<0.05) among task conditions. The first column shows a comparison of the concurrent dual-task DAS_V and LKT (V); the second column shows a comparison of the concurrent dual-task DAS_A and LKT (A); and the third column shows a comparison of the concurrent dual-task DAS_A and DAS_V (AV). The line colors indicate the differences in connectivity strength between electrode pairs, with red indicating positive differences (more information flow) and blue indicating negative differences (less information flow). The directions of the arrows represent the direct paths of interchannel information flow.

In each morning, the experimenter checked the ES of each participant and decided whether they were suitable for the experiments. The participants were asked to come to the experiment if their ES was in the suitable range of the fatigue groups (three datasets with ESs higher than 90, 3 datasets with ESs from 70 to 90, and 3 datasets with ESs less than 70). The participants normally joined the experiment within 10 hours of the call from the experimenter. All participants read the consent form and experimental description 10 minutes prior to the experiment. ESs were logged again before the participants performed the experiment. The participants were divided into three different fatigue groups with the new threshold, which is slightly different from the original proposal from Fatigue Science. The same fatigue group threshold that was used in previous work on the psychomotor vigilance task (PVT) [48] was also used in this study. There were three fatigue groups: the normal fatigue group (ESs greater than 91.5 % (ES_{mean}+ES_{std}), the high-risk fatigue group (ESs less than 72.6 % (ES_{mean}-ES_{std}) and the reduced fatigue group (remaining datasets). The EEG signals were recorded by the Synamps2 system (Compumedics Neuroscan Inc., Abbotsford, VIC) using 64 channels with Ag/AgCl electrodes and two references at the left and right mastoids (A1 and A2) according to the international 10-20 system. All electrode impedances were maintained under 5 kΩ and were recorded with a sample rate of 1000 Hz and 32-bit quantization. The participants were subsequently seated in the car in a well sound-proofed, magnitude wrap-around virtual reality driving laboratory. Participants took part in four sessions throughout the experiment for one EEG dataset, and each session contained 60 trials per task condition (LKT, DAS_V and DAS_A) in random order. Participants had a rest time of 5-10 minutes between sessions.

E. EEG data processing

Raw EEG data were subjected to bandpass filtering at 1-50 Hz before being downsized to a sample rate of 250 Hz using the EEGLAB toolbox [49] in MATLAB (version 2013b, MathWorks Inc., Natick, MA) (***Fig. 2***). Some portions of the data included artificial noise, which was manually removed. The artefact noise was defined by the raw data quality, such as the value having a strong peak compared to the remaining data.

Pre-processed EEG data were subsequently subjected to independent component analysis (ICA) [50] to decompose the independent sources of information. The function 'runica.m' in EEGLAB was used to decompose the independent components (ICs), which form the EEG data (the maximum step was 2014, and the error was less than 10^{-7}). Then, a dipole fitting routine was applied to find the IC locations. Subsequently, the non-brain components were removed (48.3±5.4 ICs) based on their IC properties, such as the location, topography, and power spectrum. The main non-brain components were the eye blindness, eye movement, muscle and sensor noise components. Next, the remaining brain components (13.5±5.3 ICs) were back projected to the EEG channel space.

Subsequently, the data were divided into task conditions with a given epoch length of [-1 2.5] seconds following the task event onset. The period from [-1 0] seconds of the epoch was used as correction baseline for all the epoch data. Then, the bad epochs under those task conditions were rejected based on their extreme values (threshold was set to 100 μV). Next, the EC

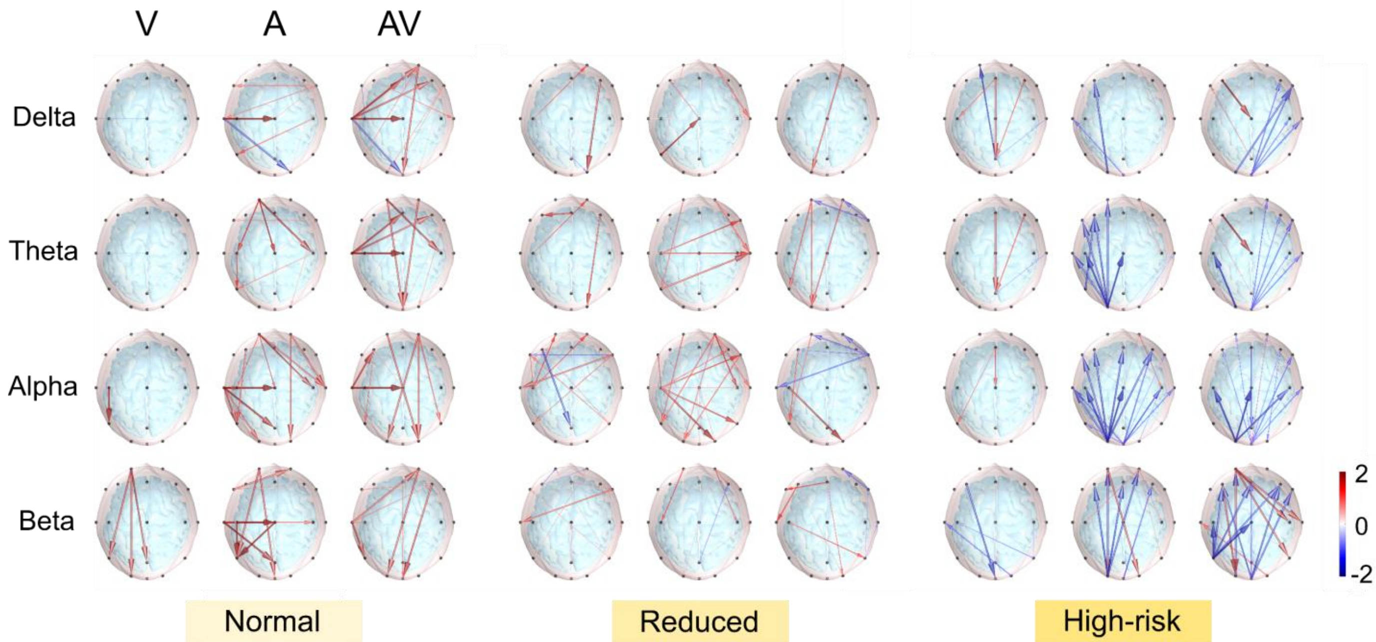

Fig. 5. Topographical comparisons of significant EEG effective connectivity differences (p<0.05) among task conditions in each fatigue group. (**a**) Normal. (**b**) Reduced. (**c**) High risk. The first column shows a comparison between the concurrent dual-task DAS_V and LKT (V); the second column shows a comparison between the concurrent dual-task DAS_A and LKT (A); and the third column shows a comparison between the concurrent dual-task DAS_A and DAS_V (AV). The line colors indicate the differences in connectivity strength between electrode pairs, with red indicating positive differences (more information flow) and blue indicating negative differences (less information flow). The directions of the arrows represent the direct paths of interchannel information flows.

levels were estimated in the channel domain from the cleaned datasets.

F. Effective connectivity

All datasets with preprocessing steps were used to calculate the effective brain connectivity. A multivariate linear dynamic (autoregressive) model was fit to the process activation time series after the stimulus onset to the aligned RT at 667 milliseconds.

Time series of EEG data were subsequently extracted for all frequency bands: delta (1-3 Hz), theta (4-7 Hz), alpha (8-12 Hz), and beta (13-30 Hz).

EC was estimated based on the Granger causality (GC) to obtain the flow of information exchanged among the brain regions. GC was introduced for the first time in econometric time series analysis [51]. Time series data set $X1_t$ was deemed Granger causal to another time series $X2_t$ when knowledge of the history of $X1_t$ could improve the prediction of $X2_t$. Multiple-channel data X at time t can be represented in stationary, stable vector autoregressive (VAR) form with order p as follows:

$$X_t = v + \sum_{k=1}^{p} A_k X_{t-k} + u_t, \tag{1}$$

where p is the model order, v is the mean of X, A_k is the model coefficient matrix, and u_t is the zero-mean white noise process. In this study, the model fitting parameter p was selected based on the Akaike information criterion (AIC):

$$AIC(p) = ln\left|\tilde{\Sigma}(p)\right| + \frac{2}{\hat{T}} pM^2, \tag{2}$$

where $ln\left|\tilde{\Sigma}(p)\right|$ is the determinant logarithm of the estimated noise covariance matrix for the VAR model with order p fit to M-channel data and $\hat{T}$ is the total number of data points (sample data points per trial x N trials).

The model fitting result was subsequently validated by three tests:

1) Whiteness test: This test was performed to ensure that the residuals of the fitted model were small and uncorrelated (white). The fitted model was evaluated based on two tests of whiteness: the autocorrelated function test (ACF) and Portmanteau test. Passing values were determined based on the Box-Pierce (BPP), Ljung-Box (LBP), and Li-McLeod (LMP) statistical tests [52, 53].
2) Percentage of consistency (PC) test: This test was used to check the fraction of the correlation structure of the modelled data compared to that of the original data [54]. A high PC indicates a good model for generating the original data.
3) Stationary of the model test: This test was performed to ensure that the original data and VAR[p] model met the stationary and stable property requirements, thus ensuring that the VAR[p] process will not diverge to infinity [52].

After the modal validation step, the causal magnitude was estimated via the following formula:

$$F_{ij} = ln\left(\frac{\overline{\Sigma_{ii}}}{\Sigma_{ii}}\right) = ln\left(\frac{var(x_t^{(i)} | x_{(.)}^{(i)})}{var(x_t^{(i)} | x_{(.)}^{(i)}, x_{(.)}^{(j)})}\right), \tag{3}$$

where F_{ij} indicates the GC from process j to process i.

Finally, Wilcoxon signed-rank tests were used to test the significance of the differences among conditions while correction using false discovery rate (FDR, $p<0.05$). Source of Information Flow (SIFT) [55] from the EEGLAB-compatible toolbox was used to estimate the EEG ECs. All data processing steps are shown in ***Fig. 2***.

IV. Results

We analysed the behavioural data based on the RT of participants. The behaviour results revealed that both task loads and fatigue states affected the RT of participants (***Fig. 3***). Then, we further examined the EC magnitude among brain regions across four frequency bands, including the delta, theta, alpha, and beta bands (***Fig. 4***, ***Fig. 5*** and ***Fig. 6***). The EC results showed significantly increased brain connectivity with increasing task load level in both the normal and reduced fatigue groups. In contrast, the opposite trend was observed in the high-risk fatigue group. The results demonstrated that fatigue and the task load affected brain connectivity.

A. Behavioural performance

The performance of the participants was assessed using the RT required to respond to the first stimulus onset, either by steering a car back into a fixed lane or pressing the bottom for the DAS task after the deviation onset for LKT. The average RTs were compared among three task conditions (LKT: lane-keeping task only, DAS_V: concurrent LKT and visual dynamic attention shifting, and DAS_A: concurrent LKT and auditory dynamic attention shifting) and three fatigue states (normal, reduced and high risk) based on a linear mixed-effects approach. As fixed effects, we entered task conditions and the fatigue state into the model. As random effects, intercepts for subjects were considered. A visual inspection of the residual plots did not reveal any obvious deviations from homoscedasticity or normality. P-values were obtained by likelihood ratio tests of the full model with the effect in question and the model without the effect in question. The results showed that the task conditions affected RT ($\chi2(1)=15.746$, $p=0.01518$), lowering it by approximately 15.8 ms; the fatigue state also affected RT ($\chi2(1)=22.463$, $p=0.0009976$), lowering it by approximately 22.5 ms. There was an interaction between the task conditions and fatigue state ($\chi2(1)=9.6777$, $p=0.04622$) (***Fig. 3***). The high-risk state was significantly different from the normal and reduced states ($p<0.001$), and DAS_V was significantly different from the LKT scenario ($p<0.01$). A post hoc pairwise analysis revealed that the LKT RT in the high-risk group was higher than the LKT RT in the normal state ($p=0.0123$), the LKT RT in the reduced state ($p=0.0011$), the DAS_V RT in the high-risk state ($p=0.0382$), the DAS_V RT in the normal state ($p=0.0069$), and the DAS_V RT in the reduced state ($p=0.0037$).

B. Comparisons of ECs for single- and dual-task conditions in different fatigue states

A computational analysis was performed with the Interactive High-Performance Computing server at the University of Technology Sydney (UTS). All comparisons used the Wilcoxon signed-rank test with an FDR-adjusted $p<0.05$. We first estimated the significant differences among task load conditions with and without considering the fatigue status (***Fig. 4*** and ***Fig. 5***). Then, we identified the significant edges to estimate the complexity of the brain connectivity network for various task loads and fatigue statuses (***Fig. 6***).

Overall, the dual-task condition exhibited increased EC across the network among the frontal, central, parietal, occipital, and temporal areas (***Fig. 4, Fig. 5*** and ***Fig. 6***) among broadband frequencies. ***Fig. 4*** shows a significant difference among task load conditions. The dual tasks displayed enhanced connectivity compared to the single tasks in both the visual DAS_V and auditory DAS_A cases (1st and 2nd columns of ***Fig. 4***). Moreover, there was an enhancement in information flow when comparing DAS_A and DAS_V (the 3rd column of ***Fig. 4***). This enhancement could be because DAS_A involves both auditory and visual modalities, while DAS_V dominantly involves visual modalities in the given task. Moreover, ***Fig. 5*** shows a significant difference among the task load conditions in three distinctive fatigue states. There was increased information flow while performing dual tasks in both the normal and reduced fatigue states. However, the high-risk state exhibited decreased

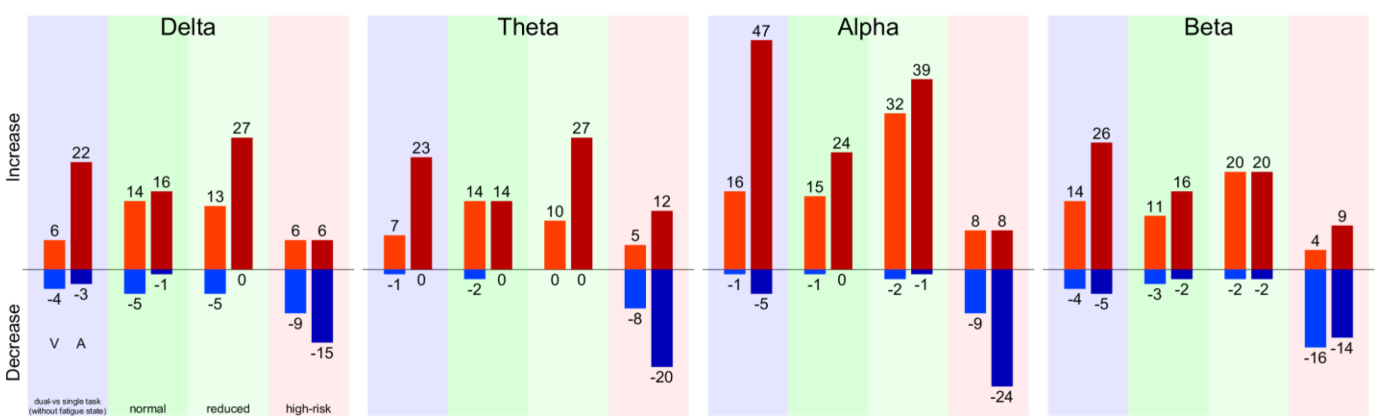

Fig. 6. Number of significantly different brain connectivity edges for the dual- and single-task conditions across brain networks (p<0.05) for the delta, theta, alpha and beta bands. The green background indicates the normal fatigue group, the light green background indicates the reduced fatigue group, the light red background indicates the high-risk fatigue group and the blue background indicates the dual- vs single-task cases without considering the fatigue state. The number indicates the number of brain connectivity edges with significant differences ($p<0.05$). The light red/blue bar indicates the increase/decrease in significant edge differences in the concurrent dual-task DAS_V vs single-task LKT comparison. The dark red/blue bar indicates the increase/decrease in significant edge differences in the comparison of the concurrent dual-task DAS_A vs single-task LKT.

information flow in multitasking conditions. Furthermore, ***Fig. 6*** shows the total significant edge difference for task load conditions fatigue states. The high-risk fatigue state clearly displayed the reduced information flow, and the normal and reduced fatigue states exhibited enhanced information flow during multitasking.

The increased and decreased edges were identified from the EC connectivity matrix after the statistical test of task conditions (Wilcoxon signed-rank test, FDR-adjusted $p<0.05$) was performed. Then, the total number of increased and decreased edges was determined (***Fig. 6***). Compared to the single-task condition (LKT), more increased edges and less decreased edges of brain connectivity were observed in the normal and reduced fatigue groups (***Fig. 5*** and ***Fig. 6***). However, there were more decreased edges of brain connectivity than increased edges in the high-risk fatigue group in the delta, theta, alpha and beta bands. Furthermore, the number of significantly increased edges in case A is higher or equal to V, indicating enhanced brain connectivity among brain regions when the task difficulty increases. Of note, the reduced fatigue group showed the highest number of increased edges across the delta, theta, alpha and beta bands in both cases V and A (with the exception of the delta and theta bands in case V). In both the V and A cases, the number of increased edges had an inverted U-shaped trend in the alpha and beta bands (***Fig. 6***). The number of increased edges in case A also displayed an inverted U-shaped trend in all bands (***Fig. 6***); however, case V exhibited a linear decreasing trend in the delta and theta bands. These results indicate the effect of fatigue on brain connectivity.

V. Discussion

Attention and cognition are complex and dynamic processes that involve multiple cortical and subcortical brain regions [56]. The resting state and task performance periods are reportedly altered at both the neuronal and system levels [56]. During the period of performing a task, the brain is typically converted to a connective network of a higher order than that in the original resting state, and the network is reorganized based on task properties. Many studies have reported increased across-network connectivity during task performance compared to that in the resting state during visual attention tasks [31, 32], cognitive tasks [30, 57], and working memory tasks [33]. We hypothesized that the across-network connectivity of the brain might be correlated with the task load. In ***Fig. 4*** and ***Fig. 5***, we applied the GC to calculate the differences in EC under different fatigue states as participants performed the LKT (single task), V (dual task DAS_V with a single task LKT) and A (dual task DAS_V with a single task LKT) tasks. The LKT requires multiple senses to safely control a car, e.g., motor resources to control the steering wheel and visual senses to observe road traffic [58]. We simulated a real situation on a street in which the participants were instructed to keep the car in a fixed lane and identify the name of an animal displayed visually or given auditorily. The DAS_V task primarily required a visual modality; however, it may have required more memory attention than only performing the LKT. Thus, the period from the concurrent stimuli event onset to the participant's first RT is critical because more brain resources are required to process dual/multiple tasks, including moving the car back into a fixed lane and processing external information for the DAS task. ***Fig. 4*** shows that the information flow was enhanced in the dual-task compared to that in the single task in the delta, theta, alpha, and beta bands. In addition, the DAS_A task employed an auditory modality, which was substantially different from the visual modality in the LKT, and the brain therefore tended to communicate more. More information flows were exchanged within this period, with the exception of connections in the left hemisphere in the delta, alpha and beta bands (***Fig. 4***). These results suggested that the communication pathways between the frontal-executive and occipito-parietal-perceptual regions were influenced by the dual-task conditions, as noted in previous studies [59, 60], which reported that enhanced connectivity was correlated with the task load.

The prefrontal area functions in working memory processes [61], and this area is active during dual tasks that engage the central executive system [62]. We hypothesized that when individuals attempt to maintain performance during demanding mental tasks (LKT-DAS_V and LKT-DAS_A dual tasks), the prefrontal region is activated. However, the capacity of the brain may be correlated with the fatigue state, as the connectivity strength was reduced as a result of the limited remaining resources in the high-risk group (***Fig. 5*** and ***Fig. 6***). However, brain connectivity related to fatigue is not well understood. Han, *et al.* [63] showed that brain connectivity based on the fatigue state during a driving task linearly increased in the delta and theta bands, and Wang, *et al.* [57] showed that compensation occurs among neural activities in response to cognitive fatigue. In this study, we demonstrated that EC varies under different states of fatigue (ref. ***Fig. 5*** and ***Fig. 6***). In the reduced and normal fatigue groups, information flows were enhanced under dual-task conditions compared to those in the single-task condition across brain regions in the delta, theta, alpha and beta bands (ref. ***Fig. 4, Fig. 5*** and ***Fig. 6***). In contrast, the high-risk group displayed the opposite trend, as information flows were reduced across all brain regions, with the exception of the frontal region (ref. ***Fig. 5*** and ***Fig. 6***). Furthermore, the distribution of the edge differences in multitasking (Fig. 6) is likely an inverse U-shape for the three distinctive states, which is in line with the results of previous studies [57, 64]. A possible explanation for this phenomenon is that there may be compensation between brain connectivity and the fatigue state of the participants. When a participant is in a reduced fatigue state, the brain may compensate for the cognitive task load [65]. However, the brain may turn into a decompensation state when the participant is in a high-risk fatigue state during multitasking [57].

Our findings provide new evidence of across-network brain connections in different fatigue states and thus serve as a promising reference for real-world applications. In contrast to the reduced and normal fatigue groups, the high-risk fatigue group displayed decreased connectivity among brain regions, particularly from or to the occipital and parietal regions. In contrast to the intuitive concept that EC increases as the workload increases, EC decreases as workload increases for individuals with high fatigue. Thus, in real-world applications, a single fatigue model cannot fit individuals with different fatigue statuses, and multiple fatigue models that can adapt to varying fatigue states are required to address individual variations.

This study also provides a view of the frontal area of the brain, an important region that may process information independent of the fatigue state. The magnitude of connectivity in the frontal region was enhanced in the dual-task compared to that in the single task in the three fatigue groups. Most importantly, this study identified the brain connectivity related to fatigue states. In future work, this study can be extended over time to assess the stability of the connectivity pattern. These variable or stable patterns could be reflected in the effect of the fatigue state on the default brain network. Therefore, the resulting features could be used to define the fatigue state of participants through the connectivity network.

In summary, this study explored dynamic EEG changes in ECs across different fatigue states during single and dual tasks. Overall, increased EC was evident across the entire brain network during dual tasks, which involved several brain regions. The EEG EC in the high-risk fatigue group decreased across all brain regions except the frontal region, which showed increased EC in the concurrent dual tasks compared to that in the single task. These brain network dynamics may have implications for understanding the complex neurophysiology of the relationship between real-world fatigue and task conditions.

VI. Conclusion

In this research, we identified the effect of the fatigue state under multitasking conditions on the results of a simulated driving experiment in a longitudinal study. There were 133 datasets recorded by combining EEG, behavioural, and physiological data over five months. The fatigue index of each participant was monitored and evaluated daily during the entire period of the experiment. The results revealed that there was enhanced information flow across the network under multitasking conditions. Furthermore, this enhancement was shown in both the normal and reduced fatigue states during multitasking; however, the high-risk state displayed a reduction in information flow. These results could be beneficial for real-life applications, and adaptive models are essential for monitoring brain patterns for varying workload demands and fatigue states. Further work can be performed by studying the dynamic connectivity patterns over time. The pattern of temporal connectivity can reflect the effect of fatigue on the neural network of the brain.

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