ELECTROENCEPHALOGRAPHIC AND PERIPHERAL TEMPERATURE DYNAMICS DURING A PROLONGED PSYCHOMOTOR VIGILANCE TASK

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ABSTRACT

Attention lapses and fatigue are a main source of impaired performance that can lead to accidents. This study analyzed both electroencephalographic (EEG) dynamics and body skin temperature as markers of attentional fluctuations in non-sleep deprived subjects during a 45 minutes Psychomotor Vigilance Task (PVT). Independent Component Analysis and time-frequency analysis were used to evaluate the EEG data. Results showed a positive association between distal and distal-to-proximal gradient (DPG) temperatures and reaction time (RT); increments in EEG power in alpha-, theta- and beta-band frequencies in parieto-occipital, central-medial and frontal components, were associated with poor performance (slower RT) in the task. This generalized power increment fits with an increased activity in the default mode network, associated with attention lapses. This study highlights the potential use of the PVT as a tool to obtain individual physiological indices of vigilance and fatigue that could be generalized to other vigilance tasks typically performed in occupational settings.

KEYWORDS

Skin temperature, sustained attention, mental fatigue, attention fluctuations, Independent Component Analysis (ICA), brain dynamics.

1. INTRODUCTION

Maintaining an optimal level of vigilance is crucial to perform many cognitive and sustained-attention tasks. However, fatigue and lapses of attention typically occur in monotonous tasks like car or locomotive driving, air traffic control or quality control monitoring. Safety should be a main concern in these tasks, and understanding the neural mechanisms associated with fatigue and lapses of attention can avoid catastrophic accidents. Typically, a gradual decline on attention can be observed along the sustained performance of a task (i.e., the time-on-task effect). In a recent review, Williamson et al. (2011) evidence a strong relationship between performance impairments and monotonous tasks which require vigilance, and highlight the need for the development of objective measures of fatigue (e.g., percentage of eye closure, EEG power frequency). Furthermore, it has been suggested that time-on-task alone is not a key predictor of crash risk in road transportation (Hanowski, Hickman, Olson, & Bocanegra, 2009). Therefore, it is also important to measure the spontaneous fluctuations that can occur throughout the task, resulting in ups and downs of the vigilant state (Huang, Jung, & Makeig, 2009). Thus, a substantial goal of research in vigilance and fatigue is to find sensitive indices of these fluctuations of attention to prevent them. The current research focused on two physiological indices, electroencephalogram (EEG) and body temperature, to test whether they can be used to predict changes in the vigilance state.

A line of research interested on measuring vigilance fluctuations has focused on the EEG patterns. For example, an amplitude attenuation of the P3 event-related potential has been linked to declines in vigilance (Käthner, Wriessnegger, Müller-Putz, Kübler, & Halder, 2014; Martel, Dähne, & Blankertz, 2014; Ramautar, Romeijn, Gómez-Herrero, Piantoni, & Van Someren, 2013). Furthermore, changes in amplitude in the main frequency bands have long been associated with low levels of vigilance and performance drops (Makeig & Jung, 1995). Specifically, a negative correlation is often found between low-frequency EEG activity (alpha, theta and delta bands) and performance in vigilance tasks demanding visuo-motor and attentional tracking. That is, as performance decreases (measured as reaction time -RT- or accuracy), the EEG power increases in these frequency bands between 1 and 12 Hz (cf. Huang, Jung, & Makeig, 2007). This correlation seems to be inverted in the beta band (12-30 Hz), although other studies found either an increment or no change in the beta band power (see Craig, Tran, Wijesuriya, & Nguyen, 2012 for a review).

The relationship between vigilance and EEG has also been studied recently by means of the Psychomotor Vigilance Task (PVT). The PVT (Dinges & Powell, 1985) is a straightforward and reliable tool for measuring fatigue in humans. In the PVT, participants have to respond, as fast as possible, to a simple visual stimulus. The inter-trial interval is randomly distributed between 2 and 10 seconds, and feedback of performance is displayed. The monotonous and unpredictable target presentation in the PVT makes subjects highly prone to lapses of attention.

Moreover, the PVT has minimal learning effects, minimizing the variability due to participants' different ability and experience (Basner & Dinges, 2011). These characteristics make the PVT a good candidate as a standard task to relate physiological variables with performance in attention demanding tasks.

Research on the relationship between EEG signals and PVT performance showed that an increment in delta power on frontal and occipital areas, and an increment in occipital theta power were associated with slower RTs and more frequent lapses (RTs above 500 ms) on sleep-deprived subjects (Chua et al., 2012; Hoedlmoser et al., 2011). It is interesting to note that frontal and parietal areas have been often related to sustained attention and, despite the scarce extant evidence with this task, one could expect performance in the PVT to rely on these brain areas. For example, Drummond et al. (2005) used functional magnetic resonance imaging (fMRI) to identify regions related to the highest and lowest performance (indexed by the 10% fastest and 10% slowest RTs, respectively) in a 10-min long PVT administered in two sessions, one with and one without sleep deprivation. They found an increased activation in the right middle frontal gyrus and right inferior parietal lobe associated with fast RTs responses for both sessions (normal sleep and total sleep deprivation), and increased activation in structures involved in the default brain network (superior frontal, medial frontal and ventral anterior cingulate gyri) in slow RTs responses. Interestingly, this increment was higher for the total sleep deprivation session than for the normal sleep session.

Attentional fluctuations during vigilance performance can be measured on two time scales: phasic and tonic. In terms of EEG frequency activity, fluctuations in the tonic scale refer to slow changes (in the order of minutes) with respect to power baseline. Therefore, sorting trials after a performance index (e.g., RT), allow us to compare periods with distinct attentional states. On the other hand, phasic analysis refers to the event-related brain activity associated to the response to the target, and can be measured in a milliseconds scale (Huang, Jung, Delorme, & Makeig, 2008). Thus, extended (tonic) periods of poor performance can present intermittent (phasic) attentional fluctuations and they both can be assessed through the EEG by means of these two different analyses.

It is important to note that the PVT was designed to be sensitive to the homeostatic pressure for sleep, and has been mainly used in sleep deprivation and circadian rhythm studies (see Lim & Dinges, 2008, for a review; Correa, Molina, & Sanabria, 2014) because the fluctuations of attention over time are most evident with sleep deprivation. Therefore, when the participants' arousal is relatively within the normal range (i.e., without sleep deprivation), the performance of the PVT might be more stable across time related to subjects with sleep deprivation, and thus, an extended PVT like the one used in the present research (45-min long), could be useful to study slowly-varying (tonic) shifts and fatigue in non-sleep deprived participants' EEG.

The current study further measured skin body temperature as an additional physiological index of vigilance performance. Although temperature is an index of metabolism, its relationship with vigilance has been known for longtime (e.g., Kleitman, Titelbaum, & Feiveson, 1938), and it is currently possible to examine this relationship with greater temporal resolution and using less invasive devices. In fact, recent studies have linked fluctuations of body peripheral (skin) temperature to vigilance. Three skin temperature measures are typically assessed: Distal temperature (measured on distal extremities, like the wrist), proximal temperature (measured near the upper-body, for example under the clavicle) and the difference between distal and proximal temperature values, i.e., the distal to proximal gradient (DPG) measure. Raymann and Van Someren (2007) manipulated skin temperature of young and elderly subjects with and without sleep problems while measuring performance in a 7-min PVT, and found that raising proximal skin temperature in 0.6°C resulted in a faster performance decrement. More recently, Romeijn and Van Someren (2011) used a modified PVT demanding fine perceptual detection and found that increments of proximal (chest) and distal (finger) temperatures were related to both decrements in response speed and more lapses, while no effect was found for wrist temperature. Likewise, they found that an increment in the DPG between finger and chest resulted in a decrement of speed and an increment of lapses. Nonetheless, the relationship between temperature and performance in a long PVT has not been evaluated yet, and although the relationship between non-central temperature measures and sleepiness remains unclear, it has been proposed the DPG temperature as the optimum measure to assess this relationship (see Romeijn et al., 2011).

The present study aimed to investigate the relationship between vigilance performance and neurophysiological markers by assessing the skin temperature and EEG spectral correlates of changes in RT, using the PVT over 45 minutes in non-sleep deprived subjects. Independent component analysis (ICA) was used to identify maximally independent neural processes and to model the fluctuations of the EEG related to fluctuations on performance. ICA can effectively obtain independent components (ICs) accounting for neural signals and artifacts such as eye movements and muscle noise (Debener et al., 2005; Delorme, Westerfield, &

Makeig, 2007; Onton, Delorme, & Makeig, 2005). The use of ICA together with a dipole-fitting approach enabled us to identify the brain regions involved in the vigilance fluctuations during performance of the PVT.

We hypothesized that RT increments in the PVT would be related to increment in the power of theta and alpha frequency bands on areas involved in the sustained attention network (i.e., parietal and right frontal areas). We also expected to find a positive correlation between the DPG and the RT (i.e., the higher the gradient temperature, the slower the responses to the PVT).

2. MATERIALS AND METHODS

2.1. Participants

Seventeen female students from the University of Granada (age range 19-28 years old, Mean age = 21.72 years old, Standard deviation = 2.50 years old) participated in the experiment voluntarily in exchange of course credits. All participants had an intermediate-type chronotype according to the Spanish reduced version of the Morningness-Eveningness Questionnaire (rMEQ; Adan & Almirall, 1991) and reported at least 7 hours of sleep in the previous night (M = 8.35; SD = 0.70). They were all right-handed, with normal or corrected to normal vision. The study was conducted in accordance with the ethical standards laid down in the 1964 Declaration of Helsinki. Participants gave informed written consent before the study and they were rewarded with course credits for their participation.

2.2. Apparatus and Stimuli

The PVT was run on an Intel Core 2 Duo PC and a 17'' CRT screen with a 60 Hz refresh rate, using E-Prime software (Schneider, Eschman, & Zuccolotto, 2001). The target stimulus was a black circle with a red edge (diameter: 9.15 degrees of visual angle at a viewing distance of 50 cm).

An online version of the rMEQ was developed to measure participants' chronotype (available at http://wdb.ugr.es/~molinae/rmeq/). Scores in this questionnaire fall into the interval between 4 (extreme eveningness) and 25 (extreme morningness).

Body temperature was measured using a temperature sensor (iButton-DS1921H; Maxim, Dallas), which has a temperature range from +15°C to +46°C and 1°C of accuracy with a resolution of 0.125°C. The sensors were programmed to sample every minute along the experimental session.

Electrophysiological activity was recorded from a 128-channel Geodesic Sensor Net of 129 Ag/AgCl electrodes [Electrical Geodesics, Inc. (EGI)], referenced to the vertex. The electrodes located above and beneath the eyes, and to the left and right of the external canthi of the eyes were used to detect blinks and eye movements. The EEG net was connected to an AC-coupled high-input impedance amplifier (200 MΩ), and impedances were kept below 50kΩ, as recommended for the Electrical Geodesics high-input impedance amplifiers. While recording, the signals were amplified, filtered (0.1 to 100 Hz band pass) and digitized with a sampling rate of 250 Hz using a 16-bit A/D converter.

2.3. Procedure

Each subject completed a one-hour length experimental session either at 11 am or 1 pm. Two sensors, one placed in the infraclavicular area of the chest and one in the ventral part of a wristband were used to measure proximal and distal temperature, respectively. Both sensors were placed on the non-dominant side of the subject before the start of the PVT, which was followed by a 10-minute acclimation period. During this time, participants completed the online version of the rMEQ, and were also asked about the amount of sleep during the previous night, the waking time, and whether they have had coffee or any other stimulant during that day.

The electrode net was then placed and the PVT was performed for 45 minutes. Participants were instructed to pay full attention to the red empty circle, and press the space bar key with the forefinger of their dominant hand as soon as the circle started to fill up in red, which happened on every trial after a random interval ranging between 2,000 and 10,000 ms in a counter-clock wise manner, and at an angular velocity of approximately 92.3 degrees per second. Participants were instructed to respond as quickly as possible, while avoiding anticipations. Feedback was provided by displaying the RT for 500 ms after the participant's response (see fig. 1).

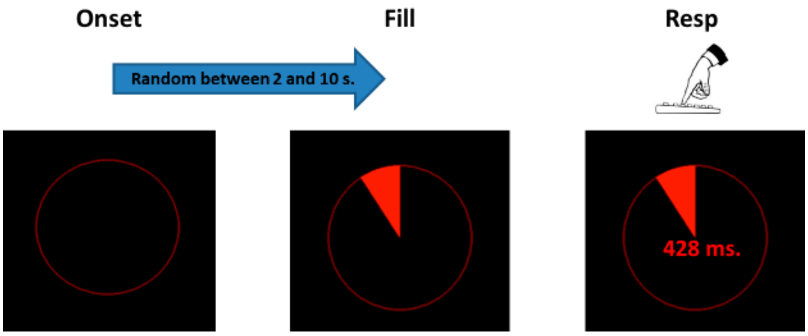

Figure 1. Sequence of event in the Psychomotor Vigilance Task

2.4. Data Analysis

The RT from the PVT was used as the behavioral measure. RTs faster than 100 ms (less than 1% of the trials) and anticipations were excluded from the analyses (cf. Basner & Dinges, 2011). To assess the relationship between temperature and performance (e.g., RT), generalized linear mixed effects models (GLMM) were used (Jiang, 2007). The GLMMs approach has been suggested to cope with problems related to non-normality of RT while avoiding the problems induced by an inverse transformation of the RTs due to "scale dependent" interactions (Lo & Andrews, 2015; Loftus, 1978). Three models were constructed for each temperature measure (i.e., distal, proximal and DPG). Every model included time-on-task (in order to isolate its effect from the attentional fluctuations). Thus, we had temperature and minute as fixed effects factors, and RT as the outcome variable. In order to match the sampling rate of the temperature measuring device, RTs from every minute were averaged. As random effects we had intercept for subject, as well as by-subject random slope for the effects of temperature and minute. Significance of the model was calculated based on likelihood ratio test of the full model against the model without the effect in question. All calculations were performed in Matlab R2015b [MathWorks, Inc.; http://www.mathworks.com/], using the generalized linear mixed-effects model class.

EEG data analyses were performed using EEGLAB v.12 (Delorme & Makeig, 2004) running under Matlab. Continuous EEG data were first re-referenced to the average and high pass filtered at 1 Hz. Powerline fluctuations at 50 Hz were removed using the *cleanline* EEGLAB plugin (http://www.nitrc.org/projects/cleanline). Independent Component Analysis (ICA) was used to decompose multi-channel EEG data into spatially fixed and temporally independent components (ICs). This study adopted the extended-infomax option of runica algorithm from the EEGLAB toolbox (Bell & Sejnowski, 1995; Makeig, Jung, Bell, Ghahremani, & Sejnowski, 1997) to separate approximately 122 source components from 122 channels (six EOG channels were excluded from the analysis). ICA assumes that scalp EEG signals are a weighted linear mixture of electrical potentials projected instantaneously from distinct independent brain sources (Makeig, Bell, Jung & Sejnowski, 1996).

The spatial origin of every IC (i.e., the equivalent dipole) was localized using the DIPFIT2 routine (Oostenveld & Oostendorp, 2002). ICs with a residual variance of dipole fitting to the scalp map exceeding 15%, and ICs with dipoles located outside the brain were excluded from further analysis (Onton & Makeig, 2009). The estimated dipole locations were co-registered to an average brain model (Montreal Neurological Institute) and to obtain a better alignment to the model, the channels were manually warped (i.e. spatially adjusted) to a 10-20 electrode system.

To obtain comparable ICs across subjects, components were semi-automatically grouped into clusters using the EEGLab standard K-means clustering method (Makeig et al., 2002; Onton & Makeig, 2006), based on the ICs scalp maps, dipole locations and the power spectra of component activations. Although the clustering algorithm tries to assign one component from every subject to every cluster, that is not always possible, resulting in a different number of trials per cluster. That is the reason why we obtained slight differences in the RTs in every cluster, as can be seen in some plots in Figure 5 and Figure 6.

The EEG data were epoched around the fill event (i.e., the moment at which the circle started to fill up), spanning 2 seconds before and 2 seconds after this event, and power spectra were calculated using a zero-padded FFT with Hanning tapers. Two types of analyses, phasic and tonic EEG dynamics, were performed for every cluster of interest.

Phasic EEG analyses

First, we computed the event related spectral perturbation (ERSP) between 2 and 30 Hz locked to the target (Makeig, 1993), in a 4 s window (2 s pre-target and 2 s post-target). The median RT from all the trials was also calculated and plotted for descriptive purposes, in order to depict the spectral perturbations related to both, the target and response events on every cluster (see Figure 5, leftmost column).

The three rightmost columns of Figure 5 show the evolution of power in individual frequency bands with respect to the optimal alert state of every subject. To do so, we baselined data from every subject separately using its own pre-target power spectra from the short-RT trials (defined as trials within the 10% fastest reaction times for every subject (see Basner, Mollicone, & Dinges, 2011). The reason to baseline each subject using its own 10% fastest trials, was to assure obtaining frequency power deviations related to the best performance of each one. Then, we combined all trials from all subjects sorted by RT, making a new baseline correction using the overall 10% fastest RTs (just for clear representation purposes), and obtained an erp-image plot of the power for theta (4-8 Hz), alpha (8-12 Hz) and beta (12-20 Hz) frequency bands on a trial-by-trial basis, obtaining thus the EEG dynamics within the epoch and along the task (see Delorme et al., 2007 for a similar analysis). Target onset and RT are also represented on the plots.

To test for significant power deviations a non-parametric bootstrap statistical analysis was performed (Grandchamp & Delorme, 2011). For every frequency, an empirical distribution of the pre-target power in the 10% short-RT from all trials was constructed by resampling 10,000 times from the original data. From this distribution, we obtained a 95% confidence interval, whose 2.5 and 97.5 percentiles were used as a threshold for significance. Thus, data with a power value outside the confidence interval was considered a significant power change for that frequency. All non-significant data samples were assigned a power value of 0 in the plot, and therefore, were represented in green. A false discovery rate (FDR) correction was applied to all statistical results.

Tonic EEG analysis

To assess frequency power changes from high to low levels of vigilance, the power was analyzed only in the pre-target data. For every trial, we obtain the average power value from the 2 s pre-target segment. Then, the same baseline used in the phasic analyses (i.e., the average frequency power from the 10% fastest trials) was applied for every trial on every subject. Finally, all trials were sorted according to the RT for every individual frequency from 2 to 30 Hz (see Figure 5, leftmost column).

The three rightmost columns of Figure 6 represent the pre-target data plotted in the left column averaged for every frequency band (i.e., averaged from 4 to 8 Hz for theta, from 8 to 12 for alpha and from 12 to 20 for beta). See also Huang et al. (2009).

To assess significance, we applied the same non-parametric approach used in the phasic analyses to data in the 2 s pre-target windows.

3. RESULTS

All subjects had an intermediate chronotype (mean rMEQ score: 13, SD: 1), and slept at least for 7.5 h during the night before the experiment. The mean time awake was 1.97 hours (SD: 0.68). None of the subjects reported having had coffee any time before the experiment.

3.1. Behavioral data

Figure 2 (left panel) shows the histogram of all participants' RT in the PVT. The distribution is left skewed with a mean of 380 ms and a standard deviation of 98 ms. There were a 91% of the RTs below 500 ms, which is the minimum RT to define a trial as a 'lapse' (Dinges et al., 1997). The 10% fastest trials had a maximum RT of 292 ms. In the right panel of Figure 2, the evolution of mean RT along time on task is plotted, showing a positive linear trend between RT and minutes on task.

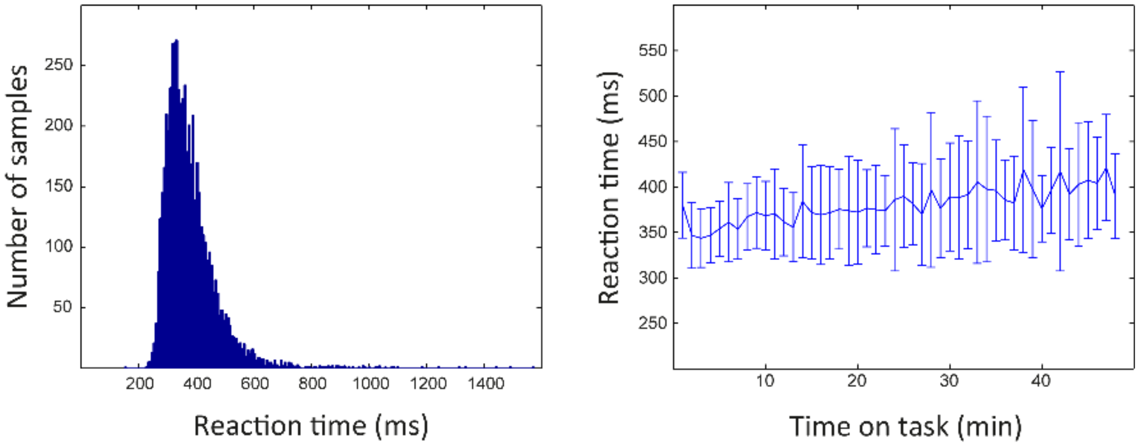

Figure 2. Distribution of RT (left) and evolution of RT with time on task (right) registered on the PVT. Error bars denote standard deviation.

3.2. *Temperature and RT analysis*

The generalized mixed effect models showed a significant positive relationship between RT and Distal (Effect = 10.21; SE = 2.81; *p* = .011) and DPG (Effect = 7.92; SE = 3.22; *p* = .036) temperature measures, that is, when Distal and DPG were higher, subjects were slower in their responses (see Figure 3). No significant effect was found for Proximal temperature (*p* = .106).

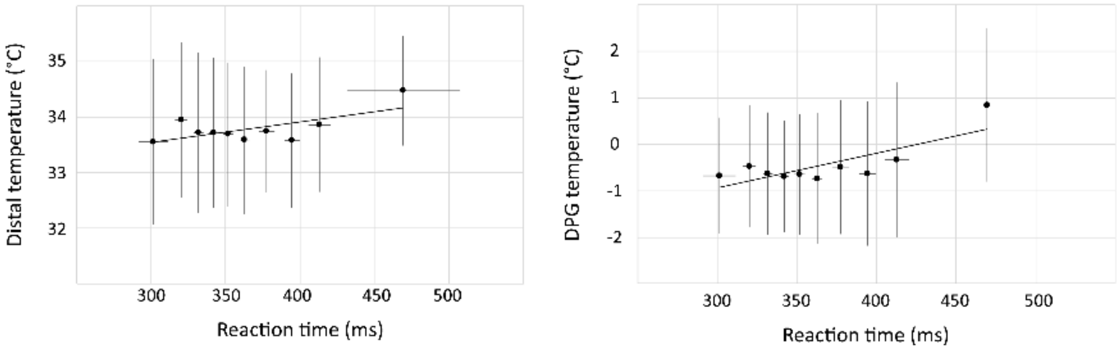

Figure 3. For descriptive purposes, RT data has been averaged in 10 percentiles and plot against temperature data (distal and DPG). Error bars represent standard deviation for RT (horizontal) and temperature (vertical). A trend line is also represented. Note that statistical analyses have been conducted on raw data..

3.3. *EEG dynamics*

From the resultant clusters obtained after grouping ICs, six clusters (i.e., left and right frontal, left and right parietal, premotor and central) were selected for further analyses based on previous literature (Chuang, Ko, Jung, & Lin, 2014; Drummond et al., 2005; Lin et al., 2010). Average Talairach coordinates for these clusters are, respectively, (-38, 44, 13), (-4, 17, 54), (28, 47, 18), (-22, -62, 0), (-7, -15, 25), (25, -52, 16), comprising the medial frontal gyrus, cingulate gyrus, left lingual gyrus, supplementary motor area and posterior cingulate cortex, regions related to the default mode network (DMN) and the fronto-parietal attention network (Hinds et al., 2013; Raz & Buhle, 2006; Weissman, Roberts, Visscher, & Woldorff, 2006). Figure 4 shows average scalp maps (top) and dipole localizations (bottom) for these clusters. Note that dipole source location cannot be as accurate as neuroimage techniques, and locations obtained should be interpreted with caution.

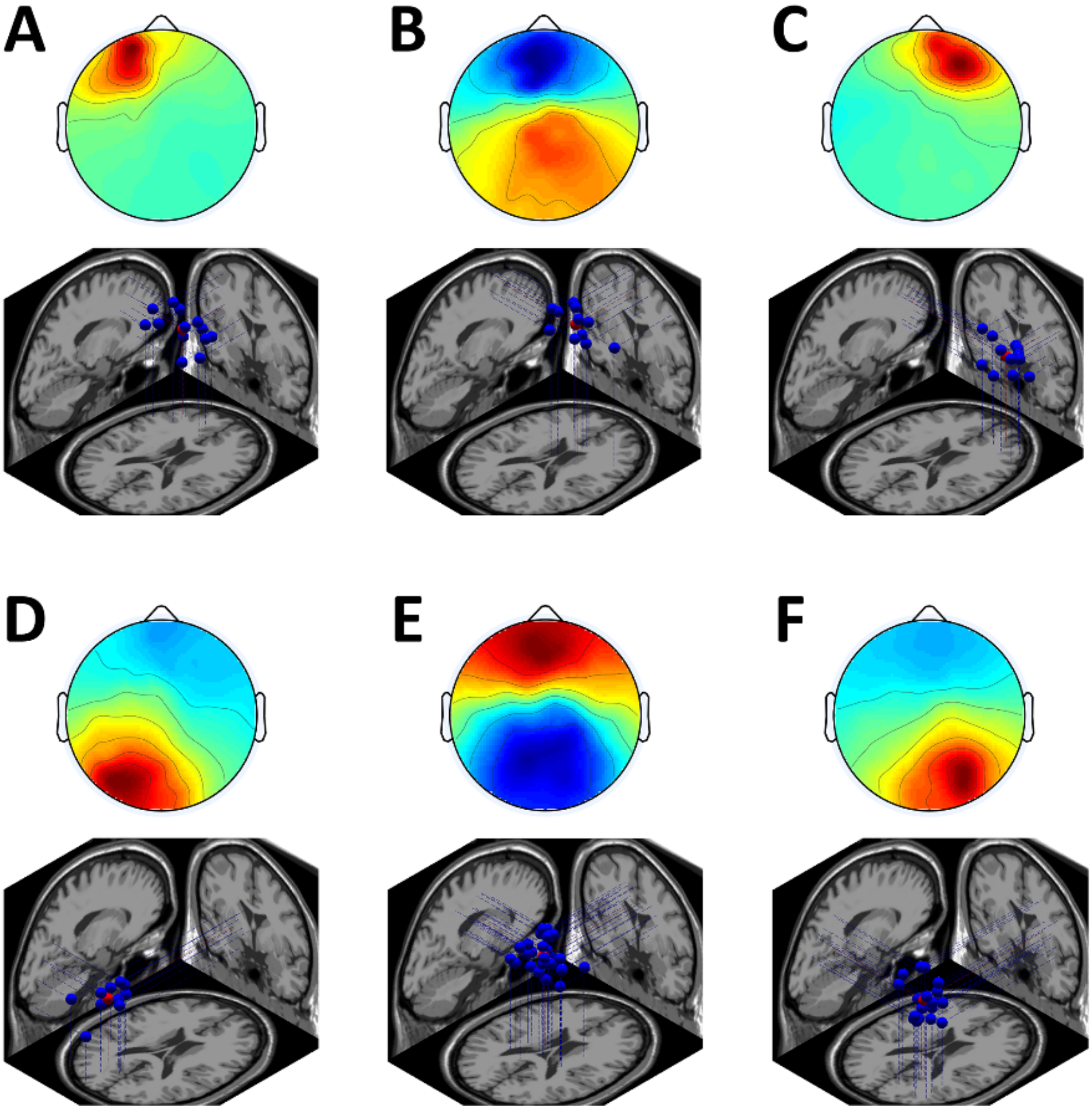

Figure 4. Average scalp maps and their corresponding dipoles obtained after grouping comparable ICs from all the subjects. Left frontal (A) and right frontal (C), premotor (B), central (E) and left parietal (D) and right parietal (F) IC clusters were analyzed.

3.3.1. *Phasic EEG dynamics*

Figure 5 shows the phasic power spectra for the six clusters of interest. Left most images are the event related spectral perturbation (ERSP) time-locked to the target onset (dashed black vertical line). The median RT is represented by the solid black vertical line. The three images to the right are the RT-sorted ERSP images for the theta, alpha and beta frequency bands. The solid black curve represents the RTs of all the trials.

The left and right parietal, central and right frontal clusters exhibited a theta burst after the target onset. This event-related synchronization (ERS) was time-locked to the target, and it was delayed around 100-150 ms in the central and frontal clusters. In the premotor cluster, theta was exclusively time-locked to the response, and synchronized around 100 ms before it. Finally, around 300-400 ms after the response, the theta synchronization disappeared for all clusters.

In the right frontal cluster, alpha showed an ERS around 200 ms after the target onset which vanished after the response. Alpha power also showed an event-related desynchronization (ERD) time-locked to the response in the right parietal, central and premotor clusters. This desynchronization immediately followed the response in the parietal and central clusters, and was delayed and less intensive in the premotor cluster.

Beta band showed an ERS time-locked to the target for the right frontal cluster and a similar behavior to alpha power in the parietal, central and frontal clusters, i.e., an ERD time-locked to the response for the parietal and central (although lower in intensity).

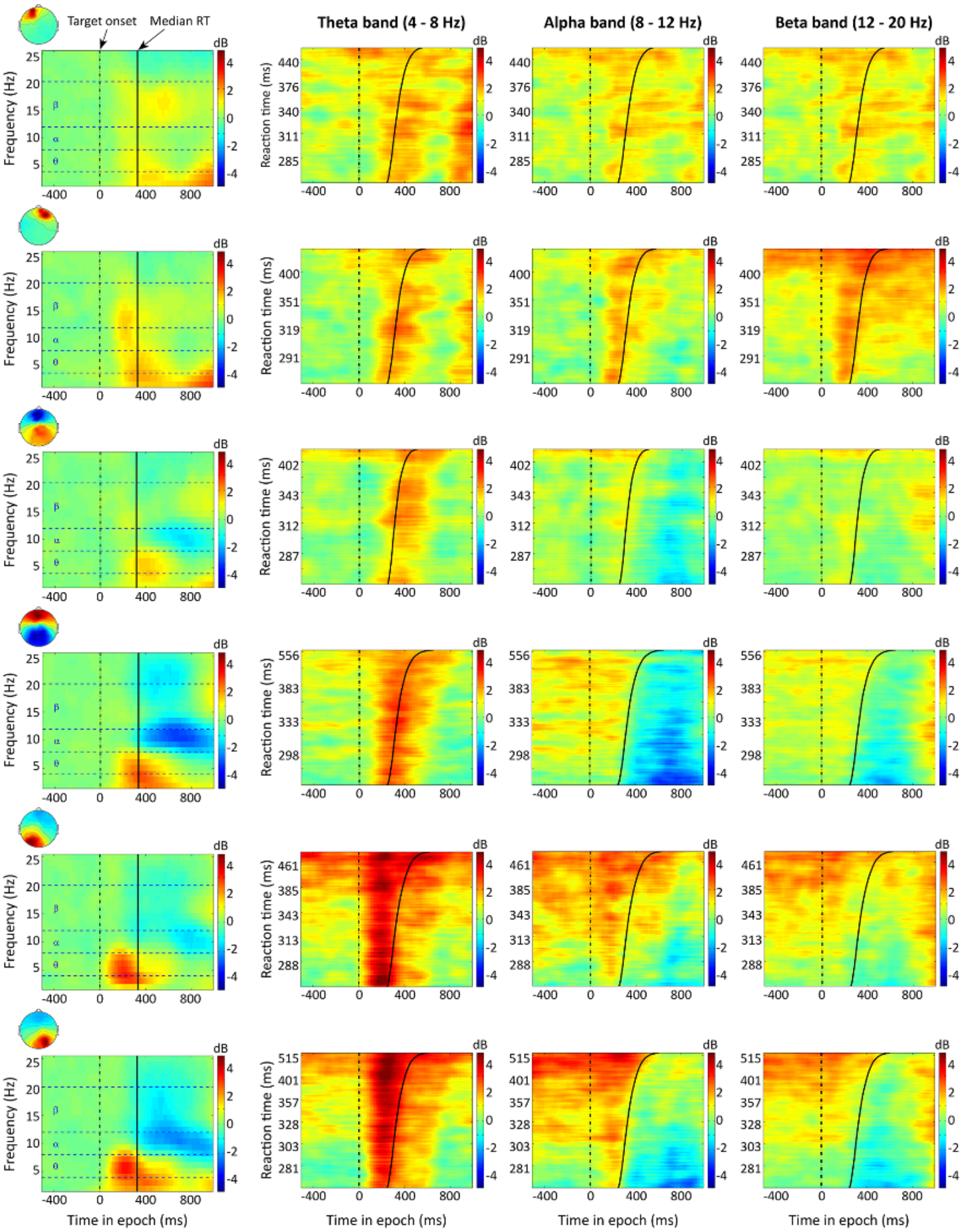

Figure 5. Phasic EEG dynamics for all clusters of interest. ERSP images (left) show the trial-averaged EEG changes in the epoch with respect to the baseline for every frequency. The three most right plots show the frequency power changes in the epoch across trials, which are sorted by RT, for theta, alpha and beta bands respectively.

3.3.2. Tonic EEG dynamics

Figure 6 shows tonic changes related to the baseline in spectral power for the six clusters of interest. The left image of every cluster shows how the mean power changes with RT for all frequencies. The three plots to the right focus on the averaged mean power for each frequency band (theta, alpha and beta). Statistical significant changes ($p < .05$) from the short-RT trials are represented on the left plots with colors other than green, and with a red horizontal line on the right plots.

In general, theta, alpha and beta bands increased with RT for all clusters except the premotor cluster, reaching a plateau for RTs greater than 500 ms. This increment was steeper in both the left and right parietal clusters, and also in the right frontal cluster for the beta band only. In the premotor cluster, the significant power increment for all frequency bands started at RTs greater than 400 ms.

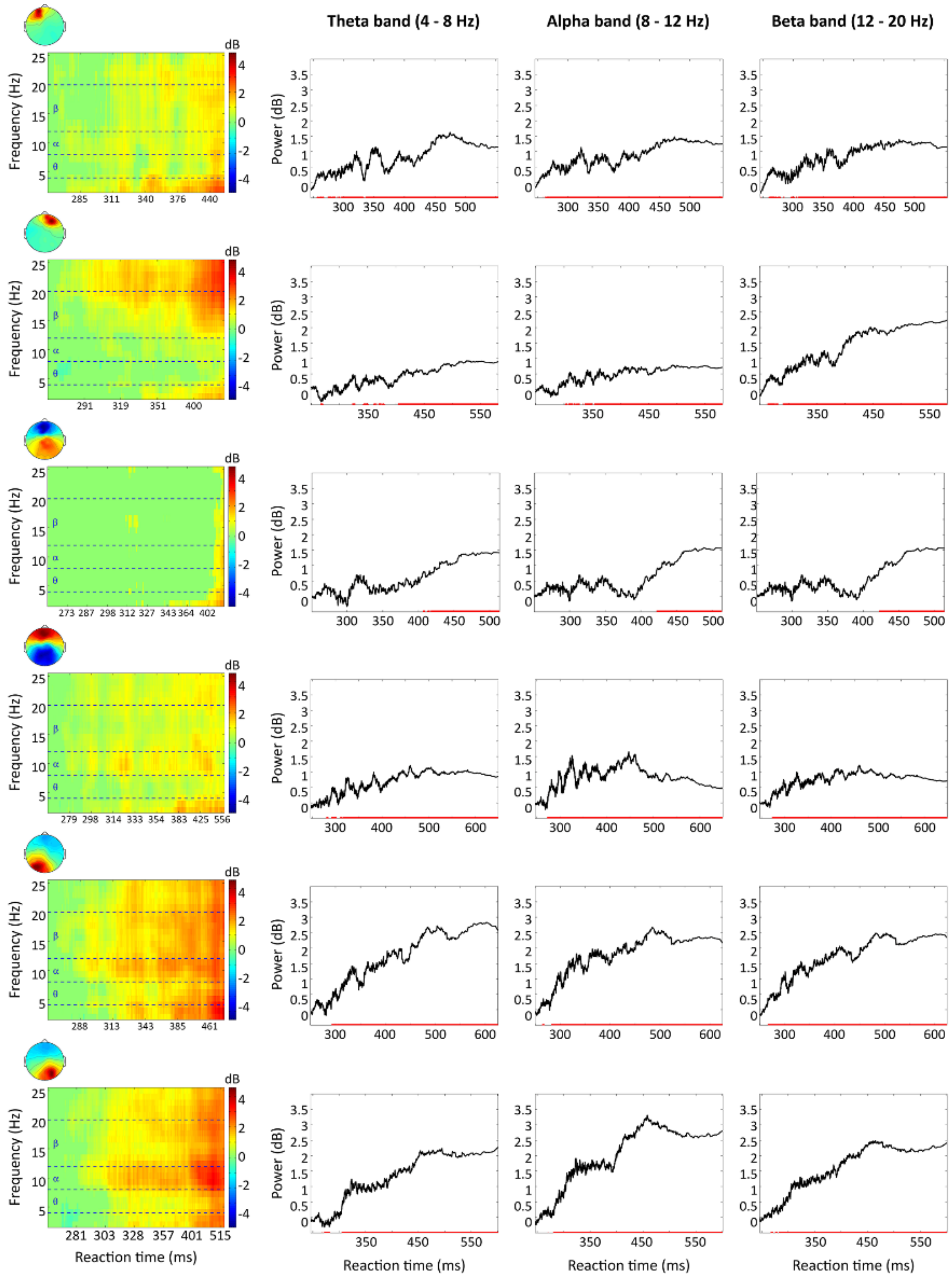

Figure 6. Tonic EEG dynamics for cluster of interest. Left image shows shifts in mean frequency power from the short-RT trials for all frequencies. The three plots to the right shows the mean power increment for theta, alpha and beta bands. Red horizontal lines represent significant changes from the power of the short-RT trials.

4. DISCUSSION

This experiment addressed physiological correlates of cognitive-state changes that span from optimal to suboptimal performances in a vigilance task. More specifically, we analyzed the relationship between skin temperature and RT, and EEG power spectra and RT in non-sleep deprived subjects performing a long PVT to predict fatigue and attentional states which are prone to cause safety issues. Slowly-varying (tonic) and event-related (phasic) changes in EEG spectral dynamics were assessed by ICA, time-frequency analysis, and nonparametric permutation-based statistics, methods for modelling fluctuations in spectral dynamics of maximally independent EEG processes during continuous task performance.

4.1. Temperature

The results of the mixed effects models showed a positive relationship between both distal and DPG temperature measures and RT, which is consistent with other studies. For example, Romeijn et al. (2012) showed a positive relationship between DPG and RT on a vigilance task. These results are also consistent with findings that relate a decrement in the core body temperature with a low vigilance state, as indexed by several performance measures, like slow RTs or subjective alertness (Kenneth P Wright, Hull, & Czeisler, 2002). This decrement in core body temperature is further considered as a mechanism to facilitate sleep onset (Kräuchi, 2007), which is achieved by means of opening skin capillaries to allow a heat flow to the outside, and results in a temperature increment in areas with a high density of capillaries, like the wrist. Therefore, an increment in distal or DPG temperatures may be related to a low vigilance state, as inferred from slow RTs in our cognitive task (PVT).

4.2. Phasic EEG dynamics

Our results showed a generalized theta burst after the stimulus presentation, which has been linked in several studies to monitoring of the task performance (see for example, Bastiaansen, Posthuma, Groot, & de Geus, 2002; Laukka, Järvilehto, Alexandrov, & Lindqvist, 1995). For parietal and frontal theta activity, two different functional roles have been attributed. Parietal theta activity would be related to the early stages of visual processing (Yordanova et al., 2002) and would contribute to the early components of the ERPs (Gruber, Klimesch, Sauseng, & Doppelmayr, 2005), whereas frontal theta activity would involve focused attention, which is increased by stimulus relevance (Deiber et al., 2007). It is also interesting to note the shorter latency of the right frontal theta ERS with respect to the premotor theta ERS, suggesting that these two different sources may also be implicated in different processes (i.e., the attentional network, and premotor processing).

Another distinct feature of the theta ERS in this study is that, unlike alpha or beta, it was observed in all clusters related to the attention network (i.e., parietal, central, premotor and right frontal). This would be in consonance with studies proposing theta to mediate in the interaction of areas spatially far from each other (e.g., von Stein & Sarnthein, 2000).

This presence of theta all over the attentional network, together with its implication in attentional processes mentioned above, suggest a key role of this frequency as a marker of performance fluctuation of the PVT, presumably mediating the communication between the areas implied in the attentional network.

Results of the present study also showed an alpha ERD following the response in the right parietal and central clusters, and around 300 ms after the response in the premotor clusters. In the right frontal cluster, there was a spindle of alpha around 100 ms after the target presentation. Alpha desynchronization has been repeatedly reported in literature in relation to attentional processes (e.g., Pfurtscheller & Berghold, 1989; Van Winsum, Sergeant, & Geuze, 1984). Klimesch and colleagues (Klimesch, Doppelmayr, Russegger, Pachinger, & Schwaiger, 1998) showed that different alpha desynchronizations were related to increments in alertness and expectancy, and Pfurtscheller (1992) found that simultaneous alpha ERD and ERS could be found at different scalp locations, which would facilitate information processing in the areas related to the task by means of idling other areas that are not involved in the task. Thus, the alpha decrement in the premotor cluster could be related to a preparation for the next trial and to control the finger movements, as its latency corresponded to the end of the feedback for the previous trial and the appearance of the red circle that marked the start of a new one (Pfurtscheller, Neuper, Andrew, & Edlinger, 1997; Pfurtscheller, Neuper, & Krausz, 2000).

More interesting is the response-related alpha desynchronization in the parietal and central clusters, which was probably related to the P300 event-related potential (ERP) component. The P300 has been associated with both attention components and the alpha ERD (Käthner, Wriessnegger, Müller-Putz, Kübler, & Halder, 2014; Sergeant, Geuze, & van Winsum, 1987; Yordanova, Kolev, & Polich, 2001). Moreover, Makeig et al. (2004) found that the posterior P300 component was time-locked to the response in a go/no-go task, similarly to our results on EEG frequency dynamics. Therefore, the alpha ERD found in this experiment was probably related to the occurrence of a response-locked P300 component.

Therefore, alpha ERD in central and parietal clusters are the most promising indices of short term performance, as they are highly linked to the RT, and alpha is highly related to attentional performance as shown above.

Finally, the beta desynchronization observed after the response in the parietal and central clusters could be related to a coherent brain state suppression due to finger movements (Makeig, 1993; Pfurtscheller, 1992).

4.3. Tonic EEG dynamics

A power spectrum increment with RT was observed in all frequency bands in all clusters, being more pronounced in the parietal clusters. In the premotor cluster, this increment started with RTs above 400ms. These results replicated an inverse relationship between power spectra and performance that has been consistently referenced in the literature with other vigilance tasks (Chuang et al., 2012; Huang et al., 2008; Huang et al., 2009; Valentino, Arruda, & Gold, 1993).

A generalized increment in alpha and theta power as performance declines might be explained by the reduction in synchronization-desynchronization patterns due to fatigue (Craig et al., 2012). This interpretation would be supported by neuroimaging studies that found an increased activity in default mode network related regions during mind wandering or attention lapses (Mason et al., 2007; Weissman et al., 2006). When the brain enters the resting-state default mode, the interactions between different areas will diminish and also will the synchronization-desynchronization patterns, increasing thus the overall frequency power. The longer the brain stays in the resting-state, the higher the power and the RT.

In addition, a lower performance in the PVT might also be consequence of a decrement in visual attention, which has often been related to tonic power increases in posterior areas (Worden, Foxe, Wang, & Simpson, 2000). Possibly, these two explanations are not exclusive, both playing a role in boosting the power spectra in the brain as performance drops.

On the other hand, increments in the frontal beta band have been explained as an attempt of participants for maintaining a level of performance despite the fatigue, that is, tonic beta increments would be indicative of participants' higher cognitive effort (Craig et al., 2012; Huang et al., 2007). Further research collecting additional measures of this cognitive effort (e.g., by self-report) could test this hypothesis.

5. LIMITATIONS OF THE STUDY

Our sample included only women, but although gender differences have been assessed in vigilance tasks (Waag, Halcomb, & Tyler, 1973), it seems that these differences are not influenced by the drowsy state of the subjects, but rather by the difference in strategy between men and women (i.e., women tend to be more accurate, while men tend to be fast, see Blatter et al., 2006). Thus, it is unlikely that a mixed sex population would have changed the results of this study in a significant way.

A more evident concern arises when registering temperature from an only female sample with no control of the menstrual cycle. Nonetheless, Shechter, Boudreau, Varin, & Boivin (2011) found no difference in maximum, minimum, circadian amplitude nor interaction between distal temperature and distal to core gradient temperature with menstrual phase. Other studies have found that circadian phase of both the core body temperature (Baker, Driver, Paiker, Rogers, & Mitchell, 2002; Shibui et al., 2000; Wright & Badia, 1999) and the distal temperature (Shechter et al., 2011) is not altered by menstrual phase. Finally, although severe premenstrual syndrome (PMS) might also affect the EEG and PVT results (Baker & Colrain, 2010), other studies have found no effect of PMS in sustained attention (Jensen, 1982; Keenan, Lindamer, & Jong, 1995; Morgan & Rapkin, 2012).

For future research, it would be desirable to increase the power by means of a larger sample size, including also male participants, and controlling for factors like menstrual phase in women.

We will also explore the possibility of extrapolating the PVT results to other sustained-attention tasks, in order to use the PVT as a predictor of performance. For this matter, we need to collect and analyze data in multiple sustained-attention tasks from the same subject.

6. CONCLUSIONS AND FUTURE RESEARCH

Nowadays the need for providing services day and night has been increased due to the demands of a 24/7 society, resulting in more than 20% of the population working outside the regular working day hours (Rajaratnam & Arendt, 2001). Shift workers, all night long bus and truck routes, air traffic control, are a few examples of tasks requiring good capabilities for sustaining vigilance and in which fatigue can be a key safety issue.

Several studies have addressed the relationship between vigilance and spectral changes in the EEG (Jung, Makeig, Stensmo, & Sejnowski, 1997; Peiris, Jones, Davidson, & Bones, 2006) on one side, and between vigilance and skin temperature on the other (Raymann & Van Someren, 2007; Romeijn & Van Someren, 2011), being both physiological variables helpful to predict the fluctuations in human performance. This study assessed whether the PVT could gather these physiological changes related to vigilance. This task requires high vigilance levels and performance does not seem to be influenced by practice, features that make the PVT a good candidate to predict vigilance decrements in daily life tasks. The use of ICA allowed us to identify maximally independent components related to the task, enhancing thus the signal to noise ratio. Both phasic and tonic EEG results showed that EEG activity during the PVT execution was related to attentional processes. As we hypothesized, we observed a pre-stimulus spectra increment together with increments in RT, especially in the theta and alpha. Also, an ERD locked to the response occurs in the alpha-band, which has been related to attentional fluctuations in vigilance tasks. Furthermore, this EEG activity was located (as IC dipoles showed) in brain areas reported to be activated in the PVT performance, like the medial frontal gyrus or the supplementary motor area (Drummond et al., 2005).

Finally, RTs in the PVT were correlated with minute-by-minute skin temperature changes. Therefore, both EEG and temperature can serve as useful indexes to anticipate and prevent performance drops. Note, however, that although the recording of body temperature is easier than the EEG, it has poorer temporal resolution.

Health and safety problems associated with fatigue are inherent to our lifestyle, and therefore, obtaining indices to predict and prevent fatigue is an important research topic. The main contributions of the current study to this topic are: (1) it shows that an extended PVT can gather attentional fluctuations in non-sleep deprived subjects; (2) it has identified several physiological markers of attentional processes demanded by the PVT (i.e., the alpha and theta frequency bands power and the distal and DPG temperature measures); and (3) it shows that such markers are common to those found in other studies that use different vigilance tasks.

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