Exercise practice associates with different brain rhythmic patterns during vigilance

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Abstract

Purpose: To investigate brain oscillatory patterns underlying prolonged attentional performance as a function of cardiorespiratory fitness in healthy young adults. **Design:** Cross-sectional study. **Method:** Two groups of participants (25 higher-fit and 25 lower-fit) were compared in terms of reaction time (RT) performance, tonic electroencephalographic (EEG) overall dynamics, and event-related spectral perturbation (ERSP) in a 60' version of the psychomotor vigilance task. Resting state EEG was also measured. A submaximal cardiorespiratory fitness test confirmed the between-groups difference in terms of aerobic fitness. **Results:** Descriptive behavioural data showed shorter RTs in higher-fit participants, but only during the first 30' of the task. Crucially, this same period was accompanied by increased theta (4-8 Hz) and upper beta (20-40 Hz) power and reduced alpha (8-14 Hz) and lower beta (14-20 Hz) suppression after the target stimulus presentation compared to their lower-fit peers, but these differences disappeared in the second part of the task. Additionally, lower-fit showed greater suppression of upper beta power than higher-fit after the cue stimulus presentation, an effect that was not modulated by the time-on-task. EEG overall dynamics results did not show significant differences between groups, although they also evidenced interesting differential brain oscillatory patterns as a function of aerobic fitness both at rest and during task performance. **Conclusions:** Cardiorespiratory fitness was related to a brain oscillatory differential response pattern over a wide range of the frequency spectrum and spatio-temporal distribution, which seems to underlie the positive association between aerobic fitness and sustained attention.

Key words: EEG, time frequency, exercise, cognition, sustained attention, physical fitness.

Introduction

Sustaining attention is a basic requirement for information processing and is crucial for proper cognitive function that allows both, adaptation to environmental demands, and the capacity to modify behaviour (1). To our knowledge, a recent study from our laboratory is the only in the brain-exercise research field that has employed brain-functioning measures to shed light on the neural mechanisms underlying fitness-related improvements in vigilance performance in young adults (2) (see Chaddock et al. (3) for evidence in children). Our findings showed that higher fitness levels were related to a time-limited better behavioural performance (i.e., shorter reaction times in the first half of the task) in a 60' version of the Psychomotor Vigilance Task (PVT), that was accompanied by larger amplitude in the contingent negative variation (CNV) potential. Higher-fit individuals also maintained larger P3 amplitude throughout the task compared to lower-fit, who showed a reduction in the P3 magnitude over time. We concluded that higher fitness levels were related to electrophysiological activity suggestive of better ability to allocate attentional resources over time and a greater attentive preparatory state.

Our previous study focused on Event-Related brain Potentials (ERPs). ERPs involve high temporal resolution and separated stimulus-locked potentials during task performance that offer relevant information about the mechanisms underlying cognitive functioning above and beyond that provided by behavioural measures. However, brain electrocortical activity is believed to be composed by diversified dynamic waveforms (4), and there is evidence pointing out that some ERP features may arise from changes in the dynamics of ongoing neural oscillations (5, 6). This evidence presumes a strong dependency between neural oscillations and ERPs, arguing that ERPs are generated, at least in part, by a reset of ongoing oscillations (6). Thus, brain oscillations play an important functional role and interact with the ERPs and, consequently, evidence from ongoing brain rhythms analysis could be transferred to findings of ERP research and vice versa (5). Additionally, the timing and direction of a change in brain oscillatory activity induced by an event or stimulus at a specific frequency band functionally reflect rhythmic changes in excitation of a population of neurons that reflect ongoing sensory, motor and/or cognitive processes (4, 7). Event-

related spectral perturbation (ERSP) analysis represent an excellent index of neural communication through which the dynamics of the power of frequency-specific oscillations are quantified and these spatiotemporal dynamics are examined providing links to associative and integrative brain functions (8).

In the search for brain function biomarkers of the fitness-related improvements in cognition, the ERSP approach is therefore an attractive proposition as it may provide complementary information to that of the ERPs. Crucially, as the ERSP contains contributions from both phase-locked and non-phase-locked oscillations, the contributions of non-phase-locked induced oscillations offer additional discriminatory information as an alternative interpretation for cortical activity while performing a cognitive task (9).

Even though the analysis of brain oscillations could further elucidate the underlying processes of the fitness-related improvements in cognition, no study so far has explored the relationship between sustained attention performance and aerobic fitness by using this approach. This is particularly noteworthy since brain oscillatory activity has been shown to be a key mechanism supporting sustained attention performance (10). In fact, time-related variations and deterioration in attention are strongly associated with specific changes in oscillatory EEG features (11). Therefore, investigating cortical oscillations can be of great interest in this area of research by leading to a deeper understanding of the exercise and cognition relationship in general, and sustained attention in particular.

Here, we stand to provide novel evidence of the relationship between aerobic fitness and neural oscillatory patterns of young adults in a prolonged sustained attention task. To this aim, we reanalysed the dataset from our previous ERP study (2) focusing on ERSP and tonic EEG overall dynamics. Based on the spectral range and spatiotemporal heterogeneity of the oscillatory mechanisms underlying the performance in sustained attention (10), and given that we did not have clear *a priori* hypotheses regarding fitness as a prone factor to modulate neural oscillations in vigilance contexts, we took an exploratory approach (12), with a bottom-up methodology by employing a stepwise cluster-based analysis.

Method

Description of the participants' characteristics, materials, EEG recording and pre-processing, and procedure can be found in the original article (2). The present study was conducted according to the ethical requirements of the local committees and in full compliance with the Declaration of Helsinki 1964 (updated in Fortaleza, 2013). All participants were informed about their right to leave the experiment at any time and gave written informed consent prior to their inclusion in each study.

Data reduction and statistical analyses: With respect to the spectral power analysis, processed EEG data segments from each experimental condition (i.e., resting state and task-related spectral power during cognitive performance) were segmented to 1-s epochs. Spectral decomposition for each epoch was computed by using Fast Fourier Transform (FFT) applying a symmetric Hamming window and the obtained power values were averaged across experimental conditions. In addition to the absolute power (AP) across experimental condition, the relative power was also examined. To this end, the percentage change in absolute spectral power from resting state to task-related EEG during cognitive performance (Δ) was calculated for each individual frequency from 1 to 40 Hz as follow: Relative power (Δ) = ((AP during task – AP resting state) • AP resting state⁻¹) • 100. We used a stepwise cluster-based non-parametric permutation analysis (Fieldtrip toolbox (13)) without prior assumptions on any frequency range or region of interest. The algorithm performed a two-tailed t-test for independent samples on all individual *electrodes (64) X frequencies (1Hz bins from 1 to 40Hz)* pairs and clustered samples with positive and negative *t*-values that exceeded a threshold (i.e., $p < 0.025$) based on spatial and spectral adjacency. Cluster-level statistics were then calculated by taking the sum of the *t*-values within each cluster. The data points from the two datasets were randomly shuffled and the maximum cluster-level statistic for these new shuffled datasets was calculated. The above procedure was repeated 4000 times to estimate the distribution of maximal cluster-level statistics obtained by chance. The proportion of random partitions that resulted in a larger test statistic than the original one determined the two-tailed Monte-Carlo *p*-value. A *p*-value of the original cluster statistic smaller than the critical Monte-Carlo *p*-value indicated significant differences between the two datasets. Spectral power main

effect of Group (higher-fit vs. lower-fit) was tested for significance at resting state period. For task-related spectral power during cognitive performance, we split the analysis into two temporal blocks (30 min each) to explore a possible time-on-task effect on the spectral power. We therefore ended up with a 2 (Group: higher-fit, lower-fit) $\times$ 2 (Block: B1, B2) design. Firstly, we tested the interaction Group $\times$ Block by applying the permutation test to the spectral power (SP) difference $SP_{B2} - SP_{B1}$. The main effect of Group was tested by applying the test to the averaged data set $SP_{B1B2} = \frac{1}{2} \bullet (SP_{B1} + SP_{B2})$. Since the aim of this study was to identify differences as a function of aerobic fitness of the participants, only significant main effects and interactions for the factor Group are reported. These comparisons were performed both for absolute and relative power datasets for each electrode and frequency bin of 1Hz without *a priori* assumptions on the region of interest or frequency range.

Regarding time-frequency analysis, task-evoked spectral EEG activity was assessed by computing event-related spectral perturbations in epochs extending from –1000 ms to 2000 ms time-locked to stimulus onset for frequencies between 4 and 40 Hz. Separate epochs were constructed for cues and targets stimuli. Spectral decomposition was performed using sinusoidal wavelets with 3 cycles at the lowest frequency and increasing by a factor of 0.8 with increasing frequency. Power values were normalised with respect to a –50 ms to 0 ms pre-stimulus baseline and transformed into the decibel scale ($10 \bullet \log_{10}$ of the signal). Again, we followed the above-mentioned 2 (Group: higher-fit, lower-fit) $\times$ 2 (Block: B1, B2) factorial design and statistical approach. Significant main effects and interactions for the factor Group were also analysed by applying the cluster-based non-parametric permutation test. In order to reduce the possibility that the type II error rate was inflated by multiple comparisons correction, we set an *a priori* criteria of averaging power values across four previously defined frequency bands: theta (4-8 Hz), alpha (8-14 Hz), lower beta (14-20 Hz) and upper beta (20-40 Hz). Additionally, to avoid an overlap with behavioural responses, we also limited the time windows of interest to the first 300 ms after the target onset (based on average behavioural response times). Note that due to a methodological limitation with the spectral decomposition algorithm, the time window of interest for the cue stimulus was limited to the first 1500ms. In this case, the algorithm performed a two-tailed t-test for independent samples on all individual *electrodes* (64) $\times$ *time*

point (cue: 0-1500ms; target 0-300ms) pairs and clustered samples with positive and negative t -values that exceeded a threshold (i.e., $p < 0.025$) based on spatial and temporal adjacency. These comparisons were performed both for cue and target datasets for each electrode and time point without *a priori* assumptions on the spatial or temporal region of interest.

Results

Resting state and task-related spectral power during cognitive performance. Resting state absolute spectral power analyses did not detect show any significant cluster for the main effect of Group ($p=0.14$). Similarly, the main effect of Group ($p=0.14$) and the interaction between Group and Block ($p=0.25$) were not significant for task-related spectral power during cognitive performance (see Figure 1). The same pattern of results was obtained regarding the relative power analysis, with no Group effect ($p>0.07$, for all clusters), and non-significant clusters for the interaction between Group and Block (all $ps \geq 0.28$).

Figure 1. Resting state and task-related spectral power during cognitive performance as a function of Group. Solid lines represent the resting state absolute spectral power and dashed lines represent the task-related spectral power during cognitive performance for higher-fit (red) and lower-fit (blue) participants. The x-axis represents the frequencies across the spectrum and the y-axis the power values for each individual frequency.

Time-frequency analysis. Cue-related spectral perturbation analysis revealed a 59 electrodes significant cluster for the main effect of Group in upper beta band with a temporal distribution ranging from 465 to 1.496 ms after the cue onset ($p=0.003$). Cue stimulus led to greater upper beta power suppression in lower-fit compared to higher-fit group (see Figure 2). The analysis of the main effects and interactions for the remaining frequency bands yielded no significant clusters (all $ps \geq 0.04$).

Figure 2. Representation of the event-related spectral perturbation (ERSP) after the cue stimulus appearance and the significant cluster in upper beta band (20-40 Hz) as a function of Group. A) Time-frequency graphs at electrode sites included within the significant cluster for higher-fit (top graph) and lower-fit participants (bottom graph); B) Representation of the group differences in upper beta band. Colorbar represents power values in decibels (dB), y-axis represents frequency in hertz (Hz) and x-axis represents time point in milliseconds (ms). Zero represents the cue stimulus appearance; C) t-values distributions (colorbar) on all individual electrodes (y-axis) and time point (x-axis) pairs and clustered samples with t-values that exceeded the threshold (i.e., $p < 0.025$) based on spatial and temporal adjacency; D) Cue-related spectral perturbation for higher-fit (red line) and lower-fit (blue line) after the cue onset. The shaded area represents the latency range where significant differences between groups were found. The electrode sites included in the significant cluster are highlighted in black in the topographic t-values plot. Y-axis represents the power values (dB), x-axis represents the time point (ms) and the topography colorbar represents t-values.

Target-related analysis for the main effects of Group did not reveal significant clusters for any of the frequency bands (all $p \geq 0.39$). By contrast, the analysis of the interaction between Group and Block showed statistically significant differences across the entire frequency spectrum. The theta band analysis exhibited a 31-electrodes significant cluster from 0 to 262 ms after the target onset ($p=0.002$). The higher-fit group showed a greater spectral power in block 1 compared to lower-fit group, although there were no group differences in block 2 (see Figure 3.a.). A 29-electrodes cluster with a temporal distribution ranging from 121 to 273 ms after the target presentation was also found in the alpha band ($p=0.006$). Again, this interaction was explained by group differences only in the first part of the task, with the higher-fit group evidencing a reduced alpha power suppression compared to their lower-fit counterparts (see Figure 3.b.). Additionally, the lower beta band analysis revealed a 40-electrodes cluster distributed from 133 to 300 ms ($p<0.001$). The higher-fit group did not evidence the lower beta suppression showed by the lower-fit group in the first part of the task, although both groups showed this slight suppression in block 2 (see Figure 3.c.). Finally, the upper beta band analysis also yielded a 50-electrodes significant cluster ranging from 145 to 300 ms after the target onset ($p<0.001$). This interaction was depicted by a greater spectral power in block 1 in higher-fit compared to lower-fit participants, while the difference disappeared in the second part of the task (see Figure 3.d.).

Figure 3. Representation of the event-related spectral perturbation (ERSP) after the target stimulus appearance and the significant clusters in theta (4-8 Hz), alpha (8-14 Hz), lower beta (14-20 Hz) and upper beta band (20-40 Hz) as a function of Group and Block. A) Time-frequency graphs at electrode sites included within the significant cluster in each frequency band as a function of Group (top: higher-fit; bottom: lower-fit) and Block (left: block 1; right: block 2); Colorbar represents power values in decibels (dB), y-axis represents frequency in hertz (Hz) and x-axis represents time point in milliseconds (ms). Zero represents the target stimulus appearance; B) t-values distributions (colorbar) on all individual electrodes (y-axis) and time point (x-axis) pairs and clustered samples with t-values that exceeded the threshold (i.e., $p < 0.025$) based on spatial and temporal adjacency; C) Target-related spectral perturbation as a function of Group (red lines: higher-fit; blue lines: lower-fit) and Block (solid lines: block 1; dashed lines: block 2) after the target onset. The shaded area represents the latency range where significant interactions between Group and Block were found. The electrode sites included in the significant cluster are highlighted in black in the topographic t-values plot. Y-axis represents the power values (dB), x-axis represents the time point (ms) and the topography colorbar represents t-values.

Discussion

In the present study we took an exploratory bottom-up approach to describe, for the first time, the relationship between aerobic fitness and neural oscillatory patterns in young adults in a prolonged sustained attention task. To this end, we re-analyze a set of data from our laboratory (2) to compare two groups of participants (i.e., higher-fit and lower-fit) in terms of tonic EEG overall dynamics and ERSP elicited by stimulus presentation over time in a 60' version of the PVT. The results of resting state and task-related spectral power during cognitive performance did not show any significant result. This result contradicts the scarce previous evidence pointing to a selective association between aerobic fitness and tonic EEG overall dynamics (14, 15). The ERSP analysis did show significant differences as a function of cardiovascular fitness, such that higher-fit group showed a greater increase in theta and reduced alpha suppression after the target presentation with respect to their lower-fit counterparts in the first part of the task, but these differences disappeared in the second block. The reader would note that the modulation of the ERSP by the time-on-task paralleled the reaction time pattern reported in Luque-Casado et al. (2), with high-fit participants outperforming low-fit participants in terms of reaction time to the target stimulus in the first half of the PVT.

It is known that early phasic theta response primarily reflects the activation of neural networks involved in allocation of attention related to target stimuli (16) and there is also evidence that strongly implicate fronto-medial theta in cognitive monitoring and control processes (17–19) thought to be crucial for sustained attention (10, 18). On the other hand, in alertness situations, alpha ERSP has been related to sensory gating mechanisms as a function of the visual and motor processes so that a reduced alpha suppression (i.e., alpha power is closer to baseline) after a target stimulus presentation in alertness contexts, seems to be linked to a greater ability to internally direct attention resulting in higher gain in sensorimotor transformation processes (i.e., between visual input and behavioral output; (20).

In a similar vein, higher-fit participants also showed no suppression in lower beta band and exhibited an increased power in upper beta with respect to their lower-fit peers during the execution of the first part of the task. Again, in the second part of the

task, the fitness-related differences disappeared and higher-fit showed the same suppression in lower beta compared to lower-fit group, while no remarkable spectral perturbation was observed in the upper beta band in any of the groups. In addition, the cue-related spectral modulations showed an interesting differential pattern as a function of aerobic fitness, in which the lower-fit showed greater beta suppression than higher-fit prior to the target presentation, although this effect was not modulated by the time-on-task.

Previous evidence has shown that event-related desynchronization or power suppression within the alpha and beta band is associated with cortical activation to meet tasks demands rather than reflect the actual performance of the system during the task, while event-related synchronization is associated with deactivated or inhibited cortical networks (9, 21). In fact, a positive relationship between reductions in beta suppression and decreased cognitive effort to meet task goals have been proposed by previous studies (9, 22). Interpreted within this framework, one could argue that the reduced lower beta suppression shown by higher-fit both to the cue stimulus throughout the task and to the target stimulus during the first half of the task in the alpha and beta bands, represent a fitness-related efficient oscillatory mode of the brain such that less cortical activation was needed to meet sensorimotor task demands.

The results of upper beta band showed a power increase during the first half of the task in higher-fit participants, although no clear power increase or suppression was shown in the second part of the task in this group or for any temporal block in the case of lower-fit individuals. It is important to note the possibility that the frequency range between 20-40 Hz could comprise mixed activity related to the beta suppression reported above (14-30 Hz) as well as localized gamma oscillations (> 30 Hz). Following this argument and according to previous evidence (23, 24), the power increase observed in this frequency band during the first half of the task in higher-fit, may be reflecting a gamma power modulation by the phase of low-frequency oscillations (< 14 Hz). Indeed, gamma band is strongly modulated by the phase of low-frequency oscillations and a cross-frequency coupling between low-frequency modulation (mainly theta) and gamma band has been shown to promote sustained attentional control (10).

Overall, taking the evidence described above, our results could therefore represent a better attentional regulation during stimulus processing in higher-fit compared to their lower-fit peers during the first half of the task. Specifically, the neural oscillation pattern of higher-fit points to a greater activation of neural networks involved in allocation of attention from the target onset, which could be facilitating an efficient integration of visual information with required motor response, finally leading to a greater visuomotor gain related to alertness during the first half of the task. This would support the only previous evidence to date using measures of brain function to determine the mechanisms underlying fitness-related improvements in sustained attention, which indicated that higher-fit participants were better at activating and adapting neural processes involved in cognitive control to meet and maintain task goals (2, 25). In addition, since sustained attention can be understood as an executive function (1), our results are compatible with a model in which theta long-range coupling indicates integration of sensory information into executive control components of motor behavior (19).

The differential oscillatory pattern as a function of fitness reported here was limited to the first half of the task. Maintaining a high attentional state is effortful and it is taxed by time-on-task (26), which has been evidenced in our study by the vigilance decrement over time in both groups. Therefore, the disappearance of the differential oscillatory pattern as a function of fitness in the second half of the task might be assigned to a drain of executive control capacities in higher-fit individuals.

The cluster-based approach allowed us to describe the spatio-temporal distribution of the neural oscillation patterns as a function of aerobic fitness without biased previous assumptions. So far, there is limited research on the individual differences in brain function and cognition as a function of fitness by using a neural oscillatory approach. To the best of our knowledge, an approach based on strong a priori spatial and/or spectral limitations is usually employed (27, 28) which could be leading to the omission of important information. Therefore, this research field would benefit from this data-driven approach to better describe the general pattern of brain oscillations in different cognitive processes as a function of fitness.

While the current study revealed group differences on stimulus-related spectral perturbations that fit well and could potentially explain the fitness-related improvements in sustained attention, these results should be interpreted with special caution. Given the descriptive nature of the present study and the absence of previous hypotheses regarding fitness in this specific context, it would be bold to make strong statements beyond mere speculation. Indeed, various factors have been described as potential mediators between the regular practice of exercise and the observed brain and cognitive changes(29). Whatever the final explanation, our study represents therefore a first step towards a better understanding of the brain dynamics underlying the relationship between fitness and cognition in general, and sustained attention in particular.

Conflicts of Interest and Source of Funding

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