Pre-stimulus antero-posterior EEG connectivity predicts performance in a UAV monitoring task

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***Abstract*—Long monitoring tasks without regular actions, are becoming increasingly common from aircraft pilots to train conductors as these systems grow more automated. These task contexts are challenging for the human operator because they require inputs at irregular and highly interspaced moments even though these actions are often critical. It has been shown that such conditions lead to divided and distracted attentional states which in turn reduce the processing of external stimuli (e.g. alarms) and may lead to miss critical events. In this study we explored to which extent it is possible to predict an operator's behavioural performance in a Unmanned Aerial Vehicle (UAV) monitoring task using electroencephalographic (EEG) activity. More specifically we investigated the relevance of large-scale EEG connectivity for performance prediction by correlating relative coherence with reaction times (RT). We show that long-range EEG relative coherence, i.e. between occipital and frontal electrodes, is significantly correlated with RT and that different frequency bands exhibit opposite effects. More specifically we observed that coherence between occipital and frontal electrodes was: negatively correlated with RT at 6Hz (θ band), more coherence leading to better performance, and positively correlated with RT at 8Hz (lower α band), more coherence leading to worse performance. Our results suggest that EEG connectivity measures could be useful in predicting an operator's attentional state and her/his performances in ecological settings. Hence these features could potentially be used in a neuro-adaptive interface to improve operator-system interaction and safety in critical systems.**

I. Introduction

The introduction of highly automated systems in many domains (automotive, aeronautics, factories) have changed the role of human operators from direct controllers to systems supervisors. Although these technologies have improved safety, they are known to induce out-of-the-loop issues for humans. Hence, these settings are challenging for the operators who ought to maintain sustained attention to be responsive and efficient at all times in such critical systems [1], [2]. Studies have shown that these task settings induce boredom which leads to divided attention and operators being distracted from the task [3], [4]. More specifically sustained attention is effortful [5] and its failures, which have been termed vigilance decrements, can lead to accidents especially when facing critical and unexpected situations [6]. ElectroEncephaloGraphy (EEG) studies have revealed evidences of reduced cortical analysis during these "mind-wandering" episodes [7], [8].

Spectral analyses have also revealed that the power in specific EEG frequency bands reflect the level of sustained attention (for a review see [9]). Previous studies have used the power of such bands to try and assess various mental states such as attentional and mental fatigue states [10]. Moreover, the analysis of the interaction between distant brain regions, i.e. connectivity, has recently gained momentum and may provide interesting perspectives to link brain activity and mental states. For instance, some studies have shown that large-scale cortical interactions underlie many cognitive functions such as decision-making, top-down visual attention or multisensory integration (for a review see [11]). Previous work has shown that connectivity between frontal and occipital electrodes might reflect top-down attentional orientation [12], [13]. Thus, the use of neural connectivity provides a promising framework to improve the on-line assessment of human operators' state for adaptive interaction purposes [14].

In the present study, we first consider classical metrics such as Power Spectral Density (PSD) to assess the degradation of attentional states induced by time on task. Our main goal is then to evaluate the relevance of an EEG connectivity metric -i.e. magnitude squared coherence- to predict the level of attentional engagement. More specifically, we focused on low frequency coherence, i.e. from 1 to 30Hz, due to the implication of θ (4-7Hz) and α (8-12Hz) frequency bands in cognitive control and attentional processes [13], [15], [16]. An experimental scenario is designed involving a 2 hour-experiment whereby the participant equipped with EEG had to supervise unmanned autonomous vehicles (UAVs).

II. Methods

A. Experimental protocol

Thirteen participants were recruited among the students of the ISAE-SUPAERO engineering school to participate in the study (5 females; aged between 25 and 30 years old). All had normal or corrected-to-normal vision and no history of neurological or psychiatric disorders. The experiment was carried ouf at the experimental facility of ISAE-SUPAERO (Toulouse, France), all participants were run on mornings between 9 and 12 am. They were placed in an experimental room with low-light and sat on a chair in front of the experimental computer with keyboard and joystick. Participants were asked to take off their watch and turn off their mobile phone. The study was approved by the Toulouse Federal University research ethics committee (CERNI) and all participants gave their informed written consent.

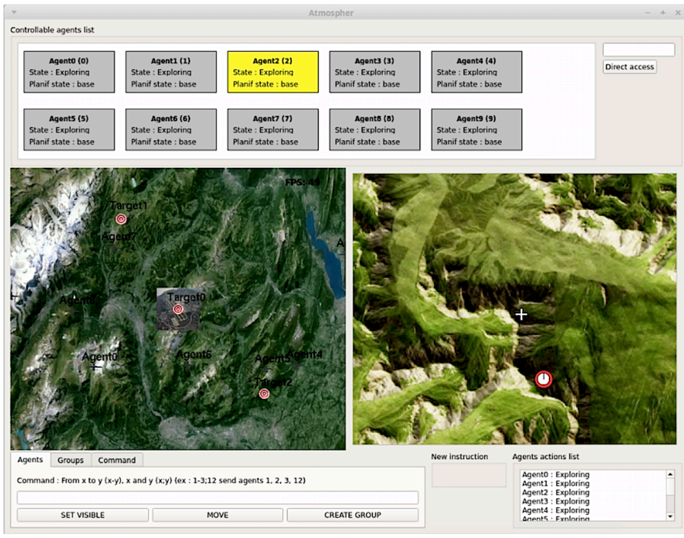

Fig. 1. ATMOSPHEr interface as displayed during the experiment. The state of ten artificial agents (i.e. UAVs) was displayed in a rectangle at the top the interface. Participants had to monitor the agent #2. In this study we were interested in Identification Task alarms (agent status blinking in yellow) which signalled the appearance of a new target in the interface's right part. These events required the participant to move the reticule toward this new target using the joystick.

The experiment consisted of a UAV supervision task implemented using the ATMOSPHEr software [17]. The ATMOSPHEr interface (Figure 1) displayed states of ten UAVs among which only one needed to be monitored (Agent #2). The task lasted 1h55min during which each agent's button could blink with three different colors: yellow, green and red:

- A green color (blinking for 5 seconds) did not require any reaction from the participant.
- A red color (blinking for 30 seconds) signalled that the agent's fuel levels were low and required the operator to make a decision on returning to the base in order to refuel or go on with the mission.
- A yellow color (blinking for 30 seconds) signalled that a target had been detected and required the participant to identify it. In order to complete the task the participant had to use the joystick to bring the reticule on the target's symbol (figure 1, lower right image, the target is represented by a white circle with a red outline).

During the whole experiment there were 7 yellow alarms and 3 red alarms. In this study we only focused on the yellow alarms to study the participants' performances since it represented more events. All alarms were always spaced by a minimum of 10 minutes. The buttons standing for other agents could also blink in red or yellow for 30 seconds or in green for 5 seconds but did not require any reaction from the participant. The response time (RT) was measured as the delay between onset of the yellow alarm and movement of the joystick. Because the goal of this study was to investigate how EEG measures can reflect an operator's mental state during a long monotonous task there were only 7 yellow events during the whole experiment. Participants had 30 seconds to react to the alarm after which the alarm was automatically turned off and no reaction time was recorded.

B. *EEG recording and preprocessing*

EEG data were recorded at 1024 Hz using the BioSemi ActiveTwo system equipped with 32 Ag-AgCl unipolar active electrodes which were positioned according to the 10-20 system. Impedance was kept below 20kΩ for all electrodes. Oculomotor artefacts were corrected using signal from the oculographic electrodes and the Second Order Blind Identification algorithm (SOBI [18]). We chose this algorithm for the source decomposition because of its non-correlation -and not mutual independence- assumption which has been shown to be more suitable for electrophysiological data [19]. The 2 sources that were the most correlated to the EOG activity were canceled. Three participants were discarded due to excessive movement during the experiment. The signal was then down-sampled to 512 Hz, bandpass filtered between 1 and 40 Hz using a 4th order Butterworth filter and re-referenced to the mastoids. Epochs of signal were extracted from the 60 seconds preceding each event (i.e. yellow alarms) and represent the trials that were analyzed. Eyetracking and cardiac activity were also recorded during the experiment but were not analysed in the context of this study (see [20]).

C. *EEG analysis*

To investigate how the EEG activity that preceded an event was correlated with RT to this event we only used data from the minute preceding that event. The main goal was to evaluate the relevance of connectivity features for performance prediction but we also assessed the relevance of power spectral density measures to compare our results with the literature. Therefore, two analyses were carried out on each trial to extract power and coherence features. Lastly, for each trial the features were correlated with response times. Details on these analyses are given below.

1) Power Spectral Density: The spectral power for each electrode, i.e. local spectral power, was computed using the Welch Power Spectral Density (PSD) estimation method on the signal of each trial using the Python library Scipy version 0.18.1. This method computes an estimate of the power spectral density by dividing the data into overlapping segments, computing a modified periodogram for each segment and averaging the periodograms. The segment length was 20 seconds with an overlap of 10 seconds. A Hann window was used to avoid spectral leakage. The PSD was computed between 1 and 30Hz with 1Hz steps.

2) Magnitude Squared Coherence: In order to compute the correlation between EEG connectivity and RT the magnitude squared coherence was computed for each subject on each trial between all channel pairs from 1 to 30 Hz using the Python library Scipy version 0.18.1. Coherence values were then transformed to relative coherence by z-score scaling them across all the electrode-electrode pairs by trial, i.e. for a seed electrode, subtracting the average and dividing by the standard deviation of the coherence across all its pairs for each trial. By computing this relative coherence score we intended to study the pattern of coherence for each electrode instead of its absolute value.

3) Correlation Analyses: After the extraction of the power and coherence features, for each trial and subject each one of the features were correlated with RT using Spearman's rank correlation. This correlation method was chosen since PSD and RT values were not normally distributed.

D. Statistical analysis

To compute statistical significance of the PSD and coherence correlations with RT we Fisher z-transformed the Spearman's rho values. Indeed, they are defined between -1 and 1 and thus aren't normally distributed. Next we used a 2-sided Student t-test. To reduce the type I errors when doing multiple comparisons we only considered effects when they were significant at $p<0.05$ and present on 2 neighbouring electrodes.

Connectivity measures have been shown to be susceptible to spuriously high values if not used with source reconstruction, or source separation methods in general, due to local activity spread, i.e. local neighbouring electrodes being coherent due to common neural sources, and volume conduction, i.e. a neural dipole being reflected at 2 distant electrodes (for a review on functional connectivity see [21]). In our analysis we didn't use source reconstruction or source separation methods since we don't intend to make any claim on neural mechanisms, their underlying neural sources or the absolute strength of some connectivity measure. With this study we merely want to assess the relevance of connectivity features as a tool to predict performance.

III. Results

A. Power spectral density

Correlation between PSD and RT showed significant effects at 2 frequencies: 11 and 12Hz. At 12Hz frontal electrodes (Fz, F3, AF3 and F8) showed a positive correlation with RT (Figure

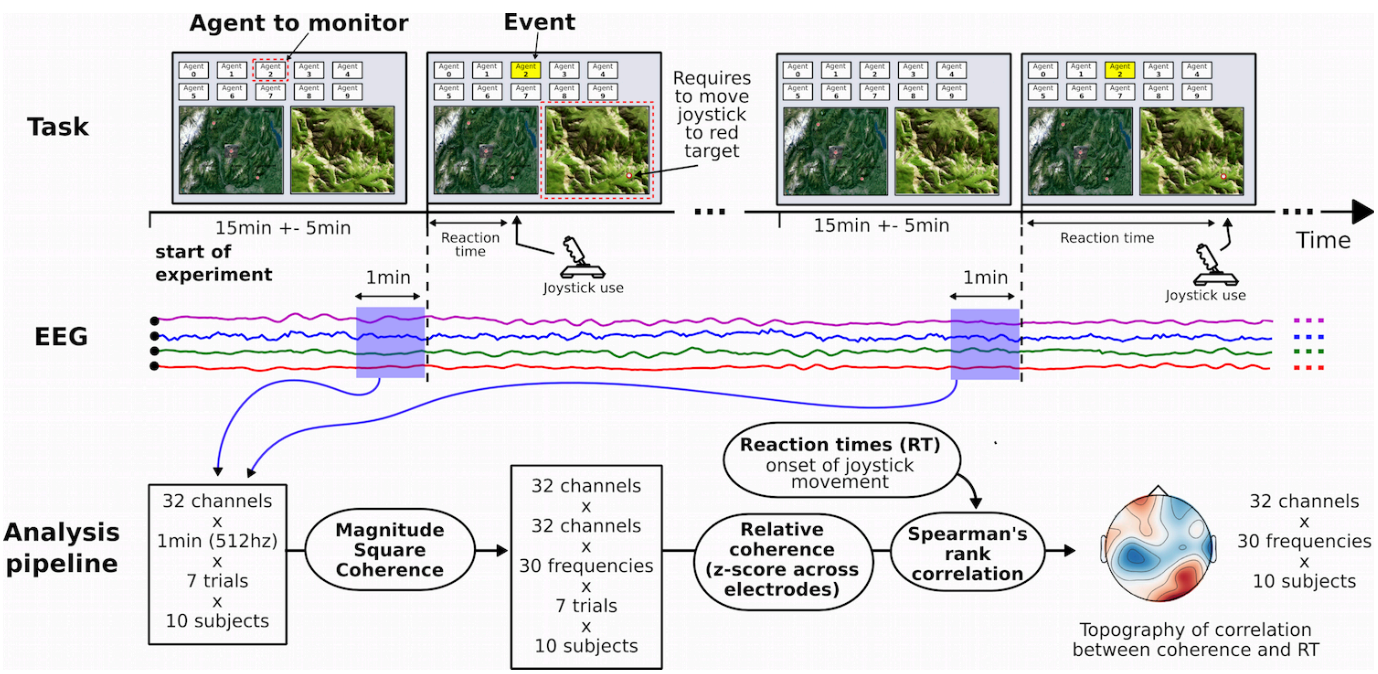

Fig. 2. Experimental paradigm and analysis pipeline. *Top*. The experimental paradigm is represented in the top part. Participants had to monitor agent #2's state. The events which were analysed in this study were yellow alarms (i.e. Identification Task alarms) which required the participant to use the joystick to move the reticule to the target (red contour circle on the bottom right part of the interface). There were 7 occurrences of these alarms which were spaced 15 minutes apart with a 5 minutes jitter. Reaction times were recorded as the delay between the onset of the alarm and movement onset of the joystick. *Middle*. We recorded EEG during the experiment and analysed data from the minute preceding each Identification Task alarm. *Bottom*. The analysis pipeline consisted of the computation of the magnitude squared coherence, we then calculated the relative coherence for each electrode, finally we correlated this relative coherence with reaction times. This procedure yielded a matrix of correlations for each electrode pair and frequency by participant. As for relative coherence, power spectral density was computed on the minute preceding Identification task alarms and correlated with reaction times which yielded a matrix of correlations for each electrode at each frequency.

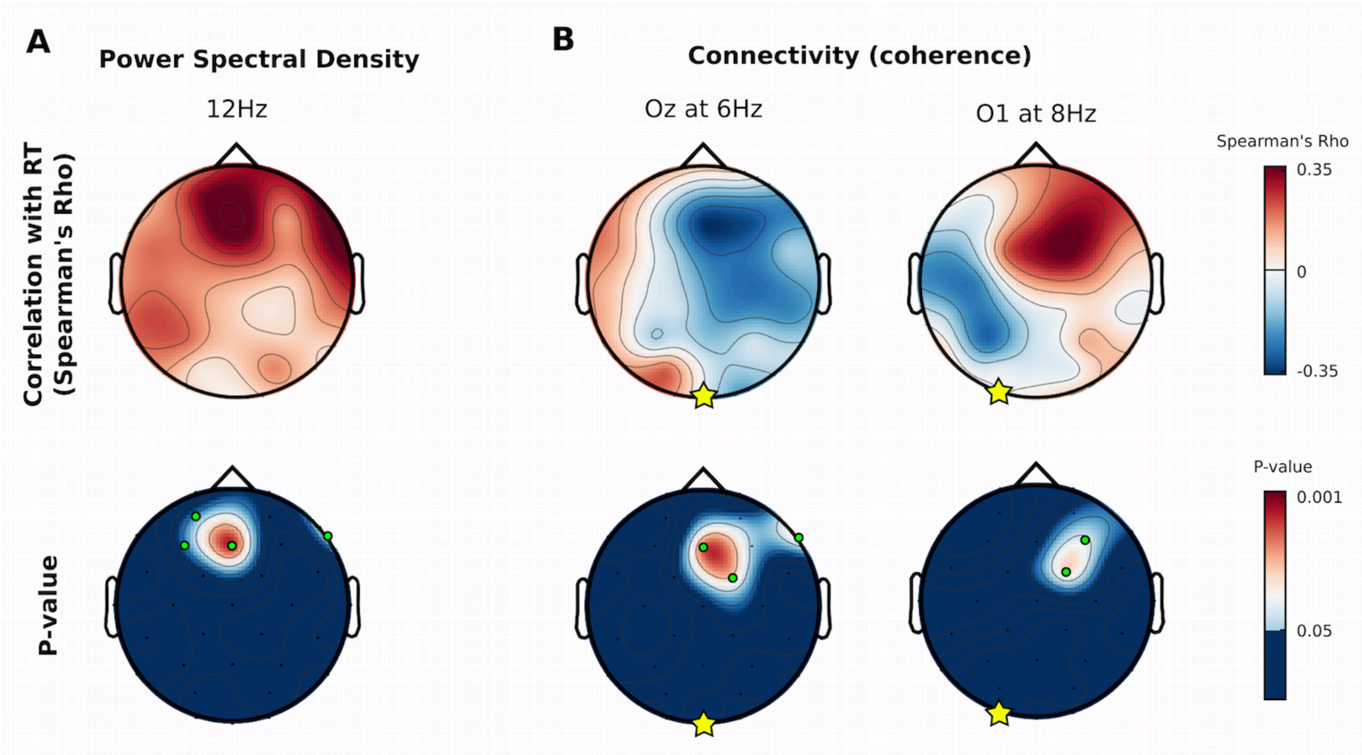

Fig. 3. Correlation of Power Spectral Density and occipito-frontal relative coherence with RT. (A) *Top*.Topography of average correlation across subjects between PSD at 12Hz and RT. *Bottom*. Significance of the correlation at each electrode. Significant electrodes depicted in green. (B) *Top*. Topography of average correlation across subjects for relative coherence from occipital electrodes, depicted by yellow star. Left part shows effects at 6Hz for Oz as seed electrode. Right part shows effects at 8Hz for O1 as seed electrode. *Bottom*. Topography of significance for the above correlations.

3A), the highest correlation being for Fz (ρ=0.44, t(9)=4.7, $p < 0.002$). This effect was also present, although to a lesser extent, at 11Hz with frontal electrodes (AF3, F3 and FC1) with F3 exhibiting the largest effect (ρ=0.43, t(9)=3.53, $p < 0.007$). This indicates that higher spectral power in the high-α band during the minute preceding an event at these electrode sites was associated with longer RT.

B. Relative coherence

Correlations between relative coherence and RT were mostly significant between occipital and frontal electrodes (Figure 3B). There were 2 significant correlation between occipito-frontal relative coherence and RT: a negative correlation in the θ band at 6Hz (Figure 4B, left), and a positive correlation in the lower α band at 8Hz (Figure 3B, right).
Concerning the negative correlation at 6Hz the strongest effect was observed between Oz and Fz (ρ=-0.36, t(9)=-4.43, $p < 0.002$) and FC2 (ρ=-0.28, t(9)=-3.93, $p < 0.004$). As for the positive correlation at 8Hz the largest effect was between O1 and FC2 (ρ=0.39, t(9)=3.86, $p < 0.004$). These effects in θ and lower α were also present for all the other occipital electrodes as seeds, although these did not reach significance (Figure 4).

IV. Discussion

The purpose of this study was to assess the relevance of electro-physiological metrics to predict decreases in performance in a UAV supervision task. In accordance with the mental fatigue and vigilance literature we found that PSD in the high-α band (11-12Hz) in frontal electrodes was positively correlated with RT. This anterior increase of α amplitude has been associated with sleepiness and the first stage of sleep [22], and a more general increase in α amplitude has been linked with lapses of responsiveness [23]. Increases in α activity in frontal and occipital sites has also been observed to occur when drivers experienced fatigue and in a drowsiness study [24], [25].

A particular interest of this study was to investigate the relevance of connectivity measures to predict human's performance under ecological settings. We observed two significant effects in occipito-frontal relative coherence, namely: a negative correlation with RT in the θ band and a positive correlation with RT in the α band.

The positive correlation in the α band between occipito-frontal relative coherence and RT is in line with the inhibition-timing hypothesis of α oscillations that has been proposed in the literature [26]. This theory posits that EEG α oscillations reflect neural inhibitory processes. Consequently, increased α amplitude in sensory cortices reflects neural inhibition and thus diminished cortical excitation leading to lower perceptual performance. The positive correlation between relative coherence in the α band and RT might therefore reflect levels of tonic alertness, i.e. intrinsic arousal that can fluctuate in the order of minutes.

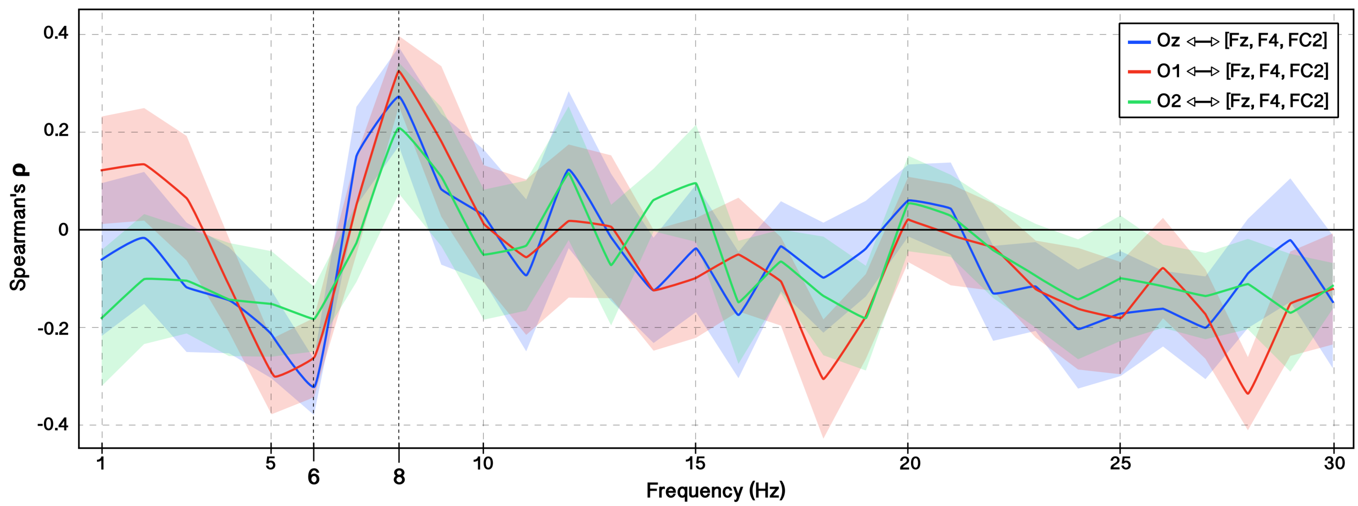

Fig. 4. Correlation between occipito-frontal relative coherence and Reaction Times between 1 and 30Hz. Spearman's rank correlation between occipito-frontal relative coherence of each seed occipital electrode and average of frontal electrodes exhibiting the 6Hz and 8Hz effects for all frequencies. Shaded area around the curves represents standard error across participants.

Higher levels of occipito-frontal relative coherence could thus index attentional/perceptual disengagement from the task.

θ band activity has been associated with error monitoring, voluntary memory retrieval and more generally with cognitive control [27], [28]. In line with this proposed role of θ oscillations, it has been shown that the Default Mode Network, a network of brain regions active while a subject is not performing any explicit task, is negatively correlated with θ band power [29]. To the best of our knowledge, the link between θ band occipito-frontal coherence and local frontal θ power has never been observed in the literature. As our result revealed that θ band coherence leads was negatively correlated with RT and thus better performance, we believe that this metric might be relevant to assess attentional engagement.

Other studies on attentional orientation have shown a negative correlation between frontal θ power and posterior α power which was predictive of performance [12], [13]. Cross-frequency mechanisms have been shown to mediate certain cognitive functions and it would thus be interesting to investigate this in future studies. Another possible lead for further analysis would be to linearly combine the PSD and relative coherence features to predict reaction times and assess if such a model yields better explanatory performance than each feature separately.

In the present study we used a fixed window of 1 minute preceding the onset of an alarm. As a next step it would be interesting to investigate how the relative coherence features relate to RT at different pre-stimulus delays. We could different delays, i.e. 30 seconds or 5 minutes, or do a continuous analysis using wavelet coherence. This would allow to characterise how the relationship between coherence and RT evolves. Other connectivity measures such as effective connectivity, i.e. directed connectivity, could also provide a more precise picture on what are the neural mechanisms involved in attentional disengagement and should be investigated in future studies.

Eventually, our next step is to implement an online passive brain computer interface (pBCI) to dynamically adapt human system interaction and to send cognitive countermeasures to overcome attentional impairment [30]. A recent review [10] has highlighted that local spectral power and evoked related potentials analyses are by far the most commonly features used by the pBCI community. We believe that connectivity measures represent promising features that could improve mental state classification accuracy and performance of pBCI systems.

V. Conclusion

In this study we evaluated the relevance of connectivity features for performance prediction in an ecological task of UAV supervision. This was done by computing the relative coherence between channels for several frequencies during the minute that preceded the occurrence of an alarm. Next, these metrics were correlated with the participants' response times. We also validated the literature on the relevance of power spectral densities for such performance prediction. The results revealed a positive correlation with RT for PSD in the high α band and a large scale relative coherence between occipital and frontal electrodes in the lower α band. Interestingly, we also obtained a negative correlation with RT for occipito-frontal relative coherence in the θ band which suggests that θ-band coherence might be a marker of attentional engagement. These results show that using EEG connectivity metrics for prediction of task engagement and performance might be possible and open interesting new avenues for research on markers of attentional states in ecological settings.

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