Investigating the neural signature of microsleeps using EEG

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Abstract— **A microsleep (MS) is a complete lapse of responsiveness due to an episode of brief sleep ($\lesssim$ 15 s) with eyes partially or completely closed. MSs are highly correlated with the risk of car accidents, severe injuries, and death. To investigate EEG changes during MSs, we used a 2D continuous visuomotor tracking (CVT) task and eye-video to identify MSs in 20 subjects performing the 50-min task. Following pre-processing, FFT spectral analysis was used to calculate the activity in the EEG delta, theta, alpha, beta, and gamma bands, followed by eLORETA for source reconstruction. A group statistical analysis was performed to compare the change in activity over EEG bands of an MS to its baseline. After correction for multiple comparisons, we found maximum increases in delta, theta, and alpha activities over the frontal lobe, and beta over the parietal and occipital lobes. There were no significant changes in the gamma band, and no significant decreases in any band. Our results are in agreement with previous studies which reported increased alpha activity in MSs. However, this is the first study to have reported increased beta activity during MSs, which, due to the usual association of beta activity with wakefulness, was unexpected.**

I. INTRODUCTION

Harrison and Horne [1] defined a microsleep physiologically as "a short period (between 5 and 14 s) of sleep identified by an EEG dominated by theta activity (4–7 Hz), and an absence of alpha activity (8–12 Hz)". Poudel et al. [2] concluded that losing the struggle to stay awake means having shifted from the drowsiness state to the sleep state. The sleep state can be divided into two parts based on duration: sleep event (> 15 s) and a MS ($\lesssim$ 15 s), with the latter falling under the definition of a complete lapse because of its specific albeit arbitrary time limits [3]. MSs can be observed through behavioural signs, such as head nodding, eye-closure, and loss of response to external stimuli [4]. MSs are usually associated with increased response-time on monotonous tasks [5] and when sleep-deprived (SD) [6], although they can occur in non-SD subjects [2, 7]. They are directly involved in many fatal accidents on the road [8]. Little research has been done to investigate the neural signature of MSs during continuous tasks with EEG [7, 9, 10]. This earlier research was limited in terms of statistical power, numbers of subjects and events, and explorations within the EEG bands.

In a study of non-SD performance on a CVT, a correlation was observed between visuomotor performance and EEG theta activity in the posterior channel (Pz), however, removing MSs from data reduced the correlation considerably [9]. Another study which looked at MS-related activities in non-SD subjects on a 2D CVT found an association between MSs and theta band originated from the bilateral frontal orbital cortex, besides an association with alpha-band originated from the bilateral anterior temporal gyri and hippocampi [10]. In a study that used a 1D CVT task, the spectral activity was increased in delta, theta, and alpha during MSs, but reduced in the beta and gamma bands [7].

The current study aimed to improve our understanding of MSs by exploring the neural signature of MSs on a 2D CVT. Hopefully, this should get us a step closer to an accurate MS detection/prediction system which can prevent many fatal accidents on the road and in other transport sectors.

II. METHOD

A. Data

This study examined EEG data collected during a previous study [2], where healthy participants performed a continuous 2D CVT task for 50-min. Whole-head fMRI, 64-ch. EEG, eye-video recording, and tracking performance were recorded simultaneously. Events of (1) a flat/disjointed tracking ($\lesssim$ 15 s), (2) a complete or partial eye closure (without blinks), and (3) clear behavioural signs of drowsiness/sleepiness were

classified as MSs [9]. If the length of a MS was more than 15 s, it was considered a sleep event.

B. Preprocessing and Denoising

This analysis was done using functions from EEGLAB software [11], plus plug-ins for special operations. As fMRI was recorded simultaneously with EEG, we removed both the gradient and pulse artefacts using the *fmrib* plug-in [12]. The data was band-pass filtered from 1–70 Hz, and down-sampled from 10 kHz to 500 Hz. The non-EEG channels were removed from the data. Using the *PrepPipeline* plug-in [13], the line noise was removed, noisy channels were identified and interpolated for consistency, and the channels were re-referenced to the average of all electrodes. The artefact subspace reconstruction (ASR) plug-in [14] was used to correct large artefacts and data discontinuities. Finally, wavelet-enhanced independent component analysis (wICA) was used to decompose the EEG signal and remove any large artefacts left based on a threshold [15]. Another run of ICA with the *ICLABEL* plug-in was performed to identify and reject non-EEG components [16].

C. Source-Localization and Reconstruction

Source-localization was carried out using FieldTrip software [17]. Following pre-processing, a subject-based brain modelling was performed by solving the forward model followed by the inverse model. We used the structural (T1) image of each subject to create an accurate forward model. Each image was initially resliced and segmented into grey matter, white matter, cerebrospinal fluid (CSF), skull and scalp. *Simbio* plug-in [18] was used to create a hexahedral head model using the finite element method (FEM) technique, which is recommended when using the T1 of each subject [19, 20]. Electrode positions were manually realigned to the head model. The head model and T1 of each subject were used to create the source model, which was then normalised to a source model template of 5 mm resolution. Only sources within the grey matter were analysed as suggested by [21]. The last step was to create the lead field from the head volume, source model, and the aligned electrodes of each subject.

We accounted for two confounding variables by regressing their effects out from each MS trial of the EEG data: (1) tracking-target-speed-related variability, and (2) poor responsive tracking, defined using a threshold calculated based on the tracking error of the first 2 min of the session. The two confounds were resampled to match the number of EEG data points. The MSs were segmented out of the EEG data, and all segments had the same length of 11 s (5 s before and 5 s after the onset of the MS). These segments were then combined as trials for each subject and were used in the inverse modelling. As we were interested in the relative difference in activity between the average MSs and their average baselines for different EEG bands, each trial was divided into event data, with a time window of 2 s starting from the onset of MS, and baseline data, with a window of 2 s before the onset.

The Fast-Fourier transform (FFT) was used to calculate the activity separately for each event and baseline from the same trial at each band of interest: delta (2–4 Hz), theta (4–8 Hz), alpha (8–14 Hz), beta (14–30 Hz), and gamma (30–45 Hz). Inverse modelling was done using the exact low-resolution brain electromagnetic tomography (eLORETA) [21] to estimate the values of the sources for each frequency within a band. Relative power was computed as $(P_e(f) - P_b(f))/P_b(f)$ where $P_e(f)$ and $P_b(f)$ correspond to the power at frequency f during MS and baseline, respectively. Estimated relative powers were averaged for each participant.

D. Group-Level Statistics

Source statistics were applied to compare the percentage relative difference to the null hypothesis of zero. Statistical analyses were performed using permutation tests [22], and the results were corrected for multiple comparisons over sources and the five bands using a family-wise cluster correction [22] of p-value < 0.01 (two-tailed).

III. RESULTS

Of the 14 subjects who had more than 2 MSs, we excluded 3 subjects due to data corruption. A final sample of 11 participants was considered for analysis, who had a total of 984 microsleeps with an average duration of 3.53 s. Our analysis showed a neural signature of MSs represented by an increase in activity in delta, theta, alpha, and beta EEG bands, where no significant change was found in the gamma band. No decrease in activity was found in any band.

The maximum increases in activity for delta-band were found over the bi-lateral frontal pole and superior frontal gyrus regions, as shown in Fig. 1.
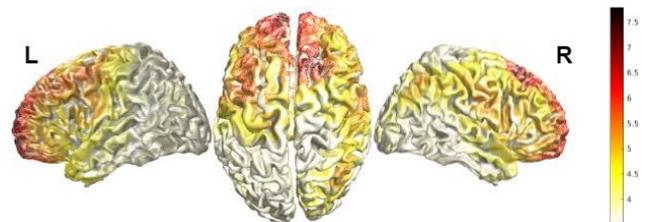

Fig. 1. Statistical maps (significant t-values) plotted on the top of a standardized brain surface for the group-level activity increase for the relative difference between average MSs and their average baselines for the delta EEG band.

Maximum increases in theta-band activity were found over the bilateral superior frontal gyrus and the middle frontal gyrus regions, as shown in Fig. 2.

Fig. 2. Statistical maps (significant t-values) plotted on the top of a standardized brain surface for the group-level activity increase for the relative difference between average MSs and their average baselines for the theta EEG band.

The maximum increases in alpha-band activity were found over the bilateral inferior frontal gyrus (pars opercularis and pars triangularis) regions, as shown in Fig. 3.

Fig. 3. Statistical maps (significant t-values) plotted on the top of a standardized brain surface for the group-level activity increase for the relative difference between average MSs and their average baselines for the alpha EEG band.

The maximum increases in beta-band activity were found over the right cuneal and bilateral precuneus cortices, as shown in Fig. 4.
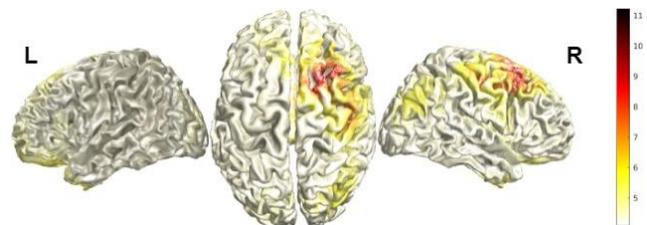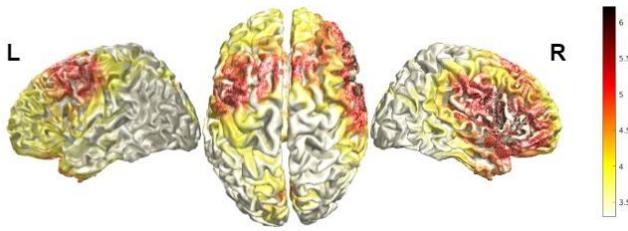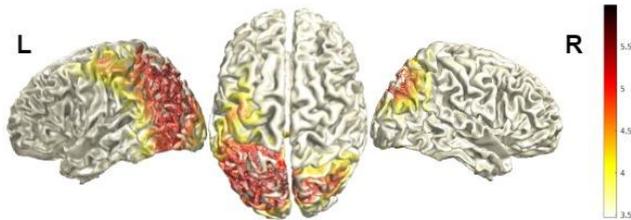

Fig. 4. Statistical maps (significant t-values) plotted on the top of a standardized brain surface for the group-level activity increase for the relative difference between average MSs and their average baselines for the beta EEG band.

IV. DISCUSSION

In our 2D CVT study, average MSs were extracted and compared to their average baselines by calculating a relative difference after averaging over trials and frequencies of interest in the subject level. A group statistical analysis was performed to explore the neural signature associated with MSs in five EEG bands: delta, theta, alpha, beta, and gamma. We found an increase in delta, theta, alpha, and beta bands activities, while no significant change in activity was found in gamma. Furthermore, no significant decrease in activity was found in any band. Our results match previous findings from a 1D CVT study, regarding the increase in EEG spectral power for MS compared to the baseline of tracking for delta, theta, and alpha bands [7]. Conversely, we found an increase in beta but no significant change in gamma. These differences may be due to inconsistencies of the neural signature of beta and gamma bands as comparable patterns were seen in EEG activity when flat spots occurred without an evident video sleep [7]. In another study, in which a 2D CVT was used, a small correlation between the visuomotor performance and the theta activity at the posterior region was found with MSs included. However, that correlation dropped when MSs were removed, indicating that MSs substantially contribute to performance fluctuations and EEG theta activity during an extended task [9]. Our results confirmed this by finding an association between MSs and an increase in theta activity.

Finding a correlation between the MSs compared to baseline and the increase of theta activity confirms a previous result by Jonmohamadi et al. [10], who used a 2D CVT task to explore the EEG to identify MS-related change of activity and find the locations of the sources of such activity. They discovered that MSs are often associated with theta activity,

which is most likely generated bilaterally from the frontal orbital cortex area. We found a similar pattern by way of an increase in theta activity in the frontal lobe. Our alpha-band results match their results of an association between MSs and an increase in alpha-band activity in the anterior temporal lobes and hippocampi, which corresponds to spindles of Stage-2 sleep.

In a flight simulator study of pilots, designed to maintain a constant/monotonous work environment, EEG spectral activity in the delta, theta, alpha, and beta bands was analysed during MSs [23]. Compared to baseline, delta activity reduced, and alpha activity increased across the scalp, but no changes were seen in the theta or beta bands. This contrasts with our results on a demanding and fatiguing CVT task, in which we found increased activity in the delta, theta, and beta bands. In a resting-state study, a reduction in activity across the scalp for delta, theta, alpha, and beta bands, from voluntary eyes-closure to eyes-opening conditions was found, reflecting the cortical processing of visual input [24]. This is in agreement with our findings on MSs, in which there is involuntarily eyes-closure. It was interesting however to see an increase in beta activity in association with MSs, given its positive correlation with resting wakefulness [25]. However, there is a negative correlation between beta activity and the total sleep time [25]. and also sleep is suggested to be characterized by a combination of both sleep-like and wake-like EEG patterns over multiple areas in the cortex [26].

Hertig-Godeschalk et al. [27] introduced MS as a stage within the wakefulness–sleep transition zone as part of their novel visual scoring criteria. Earlier research by De Gennaro et al. [28] investigated the wakefulness-to-sleep transition and found that the alpha-band spreads anteriorly. They also found increased EEG activity in the delta and theta bands, after sleep onset at the centro-frontal scalp locations. These results match our findings as we compared the MSs from onset to 2 s later versus the 2 s baseline prior to the onset.

The previous analysis of the blood-oxygen-level-dependent (BOLD) fMRI part of our study for MSs [2] was able to show activation in the frontoparietal and temporo-occipital areas, which overlapped with regions from the source-reconstructed increased activities in the delta, theta, and alpha bands for MSs. However, in contrast, we found no significant decrease in EEG activity in the thalamus region. In the same paper, additional analysis was undertaken to investigate the correlation between BOLD activity when accounting for theta and alpha EEG activities as regressors using a moving window of 2.5 s. A positive correlation was shown between the regressor representing the post-central theta fluctuations and MSs, while there was a trend of negative correlation between MSs and the regressor representing the occipital alpha fluctuations. Given the higher temporal resolution of EEG, we expected EEG to provide a more accurate representation of changes in activity. We compared each band versus the baseline of 2 s before the onset of the event in a time-locked manner. We were able to show a similar positive correlation between theta activity and MSs at the post-central area, even when theta was represented by a low temporal resolution (2.5-s) regressor, but, with the high temporal resolution, we also found a positive association between alpha activity and MSs in the occipital region.

V. Conclusion

In this study, we reconstructed cortical activity from EEG using eLORETA to investigate the neural correlates of MSs. We used individual head models and FEM for higher accuracy in the source analysis. We had a relatively large number of events across all participants (N=984), although the number of participants was limited. Our analysis compared the activity during the first 2 seconds of a MS event to a baseline of 2 seconds prior to that event. MSs have been shown to be highly associated with increased activity in the low-frequency bands (delta and theta) both with a 1D CVT [7] and our 2D CVT tasks. In addition, the alpha activity associated with MSs during a CVT has similarities with the sleep spindles of stage-2 [10]. This is supported by EEG studies exploring the transition between wakefulness and sleep [27, 28]. Surprisingly, we found increased activity in the beta band, which correlates with resting wakefulness [25], during MSs. Unlike the monotonous task used in [23], MSs appear to be associated with increased activity in multiple EEG bands in CVT which is a demanding task. Also, having decreased activity in the different EEG bands in the resting-state, when shifting from eyes-open to eyes-closed, falls in line with our results of MSs, which suggests that both involuntary and voluntary eyes-closure may have a similar EEG activity. Finally, by leveraging from the high temporal-resolution of EEG, we found a positive correlation between EEG alpha activity at the lateral occipital and posterior parietal regions.

We found increased activity in all four of the delta, theta, alpha, and beta bands. These results mostly align with the literature, with differences considered due to MS propensity being influenced by multiple factors, including fatigue [29], drowsiness [30], and type of task (1D versus 2D; continuous versus discrete; and demanding versus monotonous). In the future, the fusion of EEG and fMRI should be considered, as a combination of high temporal and high spatial resolutions to provide a more comprehensive insights into the mechanisms underlying the phenomena of MSs.

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