Characteristic changes in the EEG signals between microsleeps and preceding responsive states

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***Abstract*— This work aims at identifying characteristic features of EEG to demarcate a microsleep from preceding responsive states. The EEG signals, after reference electrode standardization technique (REST) re-referencing, were processed through a time-varying general linear Kalman filter (TVGLKF) to derive time-varying auto-regressive (TVAR) parameters. The time-varying effective connectivity measure of orthogonal partial directed coherence (OPDC) was obtained for every instant at 256 Hz. Effective connectivity matrices formed using these OPDC measures, with the scalp electrodes as nodes were processed further using graph theory. Community-based measures were investigated and statistical significances compared. Non-parametric Wilcoxon signed rank test was used for significance analysis, with Cohen-type and Common Language effect size (CLES) as measures of effect sizes. The results showed a decrease in directional modularity from anterior to posterior, in theta, alpha, and beta bands in microsleeps. The alpha band showed the highest significance with a Cohen-type effect size of 1.25 and a median percentage difference of 23% across subjects, with a range of 13-28%. Flexibility and integration also decreased with average percentage of 25% (17–35%) and 20% (16–32%), respectively, while recruitment increased on an average of 11% (3–16%), wherever significant across all bands. These community-based measures can help characterize and explain changes in brain mechanisms, and can also serve as potential biomarkers for microsleep detection.**

I. Introduction

A microsleep is a temporary episode of sleep (0-15 s) in which an individual is unconscious and unresponsive [1], [2]. People who experience microsleeps are often unaware of them, instead believing themselves to have been awake or to have temporarily lost focus.A well cited example for a catastrophe attributed to microsleep is the Waterfall train disaster in 2003 [3]. It is imperative that microsleeps are studied, analyzed, understood, and characterized, to aid in their detection or even prediction in order to reduce microsleep related incidents.

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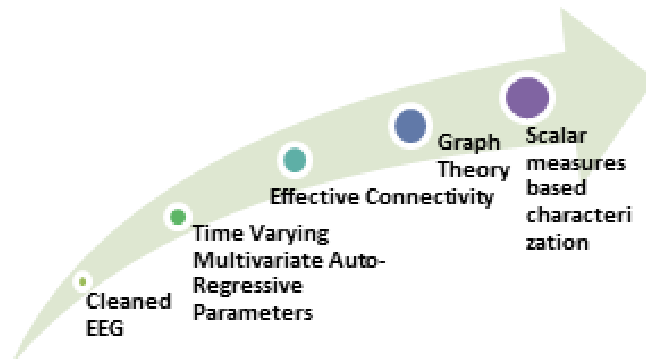

Fig. 1. Steps involved in processing EEG signals to obtain scalar measures for microsleep event characterization

This work is based on effective connectivity (EC) based graph construction and analysis. Although a substantial amount of work was involved in [4], there is lot of uncharted territory to be explored. Firstly, EC can be explored at the sensor level, which might give insight into global brain dynamics rather than specific cortical areas. Other measures of EC, such as time-varying orthogonal partial directed coherence (tv-OPDC) and directed direct transfer function (dDTF), can be explored towards understanding brain circuits. Weighted-directed graph theory can be deployed for analysis of brain networks using more complex network measures as opposed to binary-undirected based measures. Both of these static and dynamic graph techniques can be investigated. Lastly, approaches such ascommunity detection, core-periphery, and eigen-connectivity based analysis might lead to a deeper understanding of the mechanisms underlying microsleeps. Community detection involves dividing the electrodes/nodes of the brain network into non-overlapping modules based on a cost function. The quality of division is represented by level of modularity. Community evolution measures indicate how the modules evolve over time. Here, an effort is made to focus on these lines for identifying community-detection-based measures, contrasting microsleep events from preceding responsive EEG.

II. Methodology

The current work involves characterization of EEG signals before and during microsleeps using effective connectivity (EC) based brain networks. Fig. 1 represents the steps involved in processing EEG signals to obtain scalar measures proposed for microsleep event characterization. Time-varying orthogonalized partial directed coherence (tv-OPDC) was chosen for analysis, due to its ability to nullify the effects of volume conduction. This technique reveals synchronous exchange of information between electrodes (sensor-space) and EC is investigated in theta, alpha, and beta bands. The EC matrices are weighted-directed graphs, processed using graph theory to analyze community-detection-based measures. Only the eight subjects who had at least one microsleep in at least one of the two sessions were considered for analysis. The Gold standard labelling of Study A included 'Responsive', 'Unknown', and 'Microsleep'. Unknown states could not be classified definitely as microsleep or responsive states. Hence, all analyses on Study A exclude the Unknowns. For all statistical analysis, the microsleeps were contrasted with the last ten definitive responsive epochs as shown in Fig. 2. Across-events boxplots shows the range of p-values and Cohen-type effect sizes [5] for the eight subjects, about the median. Across-subjects boxplots shows the range of p-values and Cohen-type effect sizes for all 16 electrodes. The table Table I shows both Cohen-type as well as the common language effect sizes (CLES).

A. Data

The Study A dataset was the first behavioral and EEG dataset to be acquired in NeuroTech's Lapse research. The main reasons for choosing Study A for initial experimentation for this work is that this dataset has been extensively used in prior research work from which several findings and characterizations were revealed on microsleeps, thus establishing a baseline standard, especially for microsleep detection [2]. In Study A, 15 healthy subjects aged 18-36 years were recruited. None of the subjects had a current or previous neurological or sleep disorder. All of the subjects reported that they had slept normally the previous night (mean = 7.8 h) and, hence, were considered non-sleep-deprived. All subjects performed a 1-D continuous visuomotor tracking task in two sessions, each session lasting one hour. The Institutions's Ethical Review Board approved all experimetal procedures involving human subjects.

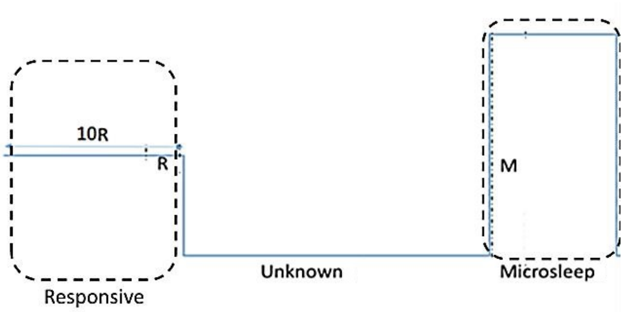

Fig. 2. A typical RUM frame of a microsleep event

B. EEG pre-processing

Sixteen-channel EEG signals were recorded at 10-20 international standard positions (Fp1, Fp2, F3, F4, F7, F8, T3, C3, T4, C4, T5, T6, P3, P4, O1, and O2, with linked ears as reference), pre-processed using a zero-phase FIR filter, and bandlimited to 1–70 Hz. The 50 Hz powerline interference was removed using a notch filter. Bad channels were rejected and interpolated using the EEGLAB software. The EEG signals were then re-referenced to common Average Reference (cAR). Other artefacts, such as EMG, EOG, EKG, etc., were removed by performing independent component analysis (ICA). Poor components were removed and the EEG was back projected to channel space. For analysis of EC, cAR may not be ideal, as it involves subtraction of average potentials from all electrodes [6]. This may lead to some spurious ghost EEG in locations where there was originally no signal present, leading to a false participation of the electrodes in EC-based brain network. Hence, re-referencing via reference electrode standardization technique (REST) [7] was performed to mitigate these specious effects. In this, the reference of the EEG signal is shifted to an infinite neutral point (ideal). An EEGLAB plug-in, REST [7], was used for re-referencing the EEG signal. The EC analysis was done in sensor-space and not in source-space.

C. Effective connectivity based brain network

Time-varying multi-variate Granger causality (tv-MVGC) analysis was performed using adaptive general linear Kalman filter single trial (GLKF-ST) approach [8] to explore coherent brain networks in the theta, alpha and beta bands. An update coefficient of 0.3 was used as in [4]. Time-varying OPDC measures [9] were derived from time-varying multi-variate auto-regressive parameters. These OPDC measures at 256 Hz serve as the edges of weighted-directed brain networks whose nodes are electrodes. The significance of the EC edges or links was assessed using a surrogate dataset, by comparing the estimated connectivity with the null distribution, setting the significance level at $p<0.05$. Only significant links were included in the subsequent analysis and in the calculation of EEG indexes of connectivity.

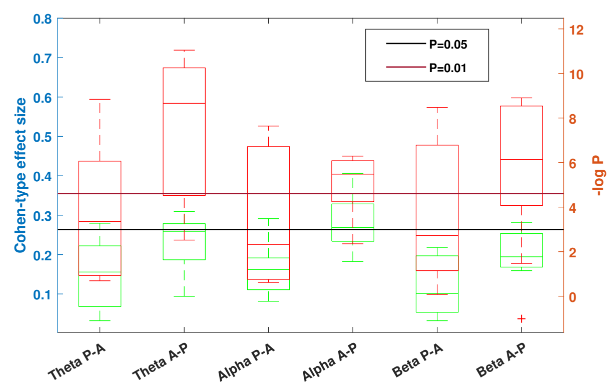

Fig. 3. Across-events modularity analysis with Cohen-type effect sizes and p-values in green and red, respectively.

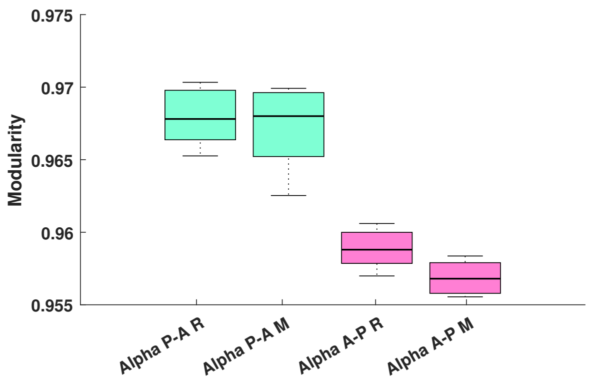

Fig. 4. Boxplots of modularity in alpha band in posterior to anterior (P-A) and anterior to posterior (A-P). 'R' represents the preceding responsive states and 'M' represents the microsleep states

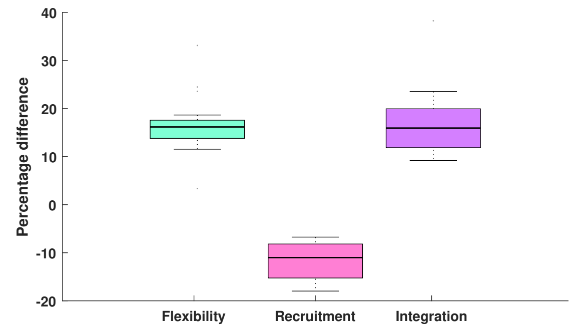

Fig. 5. Boxplots of medians of average percentage differences of flexibility, recruitment, and integration between responsive and microsleeps, across subjects, for all electrodes in alpha band (A-P)

D. Community Detection - Graph Theory

The weighted-directed brain networks, obtained at 256 Hz, were processed for community-based measures [10]. Community detection was explored for finding the key topological differences between the microsleeps and preceding responsive states. The communities for every epoch at 4 Hz (0.25 s), containing 64 temporally-ordered graphs were obtained by Newman-Girvan's multi-layer modularity [10], followed by Louvain's post-processing [10]. Since direction also contains substantial information and the literature associates anterior-to-posterior/posterior-to-anterior directional connectivity to different states of consciousness [11], the adjacency matrices were split into two by separating the lower and upper triangular values. The upper triangle represents the posterior-anterior flows and the lower triangular values represent anterior-posterior information flow. Directional community detection was performed by processing both the matrices derived separately after symmetrizing the same. In addition to modularity, three community-evolution metrics analyzed were:

- Flexibility [11]
- Recruitment coefficient [11]
- Integration coefficient [11]

E. Statistical Analysis

Two levels of statistical analysis, 'Across-events or Within-Subject' (Level 1) and 'Between-Subjects' (Level 2), were carried out to identify features that significantly differed between microsleep and preceding definitive responsive epochs. The non-parametric Wilcoxon signed rank test was used for analysis. Features which were consistently different at both levels serve as potential features for classifying the microsleep and responsive states/events, to detect or predict microsleeps. They also convey physical meaning of brain network patterns, which can help in understanding brain mechanisms, during responsive and microsleep states/events.

III. Results

The modularity measure of the multi-layer Newman-Girvan community detection was found to be significant across events for all subjects in anterior to posterior (A-P) direction, in theta, alpha, and beta bands (Fig. 3). Across-subjects analysis also brings out the same with good Cohen-type and common language effect sizes (Table I). A decrease of 23% (13–30%) in modularity was observed in alpha band with a Cohen-type effect size of 1.25 in A-P direction. Also, theta and beta bands showed 27% (4–61%) and 17% (3–26%) decreases in modularity with Cohen-type effect sizes of 0.65 and 0.92, respectively. An overall decrease in modularity was observed in the A-P direction in the alpha band (Fig. 4) with similar results in theta and beta bands. Fig. 4 shows the boxplots of modularity values for alpha in A-P about median. Similar results were obtained for other bands and directions.

Across-subjects analysis shows a significant decrease in flexibility in microsleeps for most of the electrodes in all bands/directions. The p-values are very close for almost all electrodes (Fig. 6). Flexibility decreased about 24% (5–37%), 25% (13–31%), 25% (13–36%), 23% (11–30%), 26% (11–39%), and 25% (6–30%), in theta P-A, theta A-P, alpha P-A, alpha A-P, beta P-A, and beta A-P respectively. The recruitment coefficient increased during microsleeps for most electrodes about 13% (9–21%), 14% (6–26%), 15% (8–34%), and 9% (4–30%), in theta P-A, theta A-P, alpha P-A, and alpha A-P respectively. There were no changes in

TABLE I
Across-subjects Modularity Analysis

Band	Direction	P	CLES	%Diff	Cohen-type
Theta	P-A	0.055	0.62	1	0.38
Theta	A-P	0.008	0.68	27	0.65
Alpha	P-A	0.109	0.48	-4	0.27
Alpha	A-P	0.008	0.86	23	1.25
Beta	P-A	0.523	0.55	10	0.11
Beta	A-P	0.016	0.7	17	0.92

the beta band. Overall, across all bands the recruitment coefficient increased 11% (9-15%), among the electrode positions that showed significance. Also, the integration coefficient decreased for most electrode positions about 17% (10–28%), 21% (12–30%), 27% (20–52%), 22% (11–38%), 20% (9–40%), and 19% (12–28%), in theta P-A, theta A-P, alpha P-A, alpha A-P, beta P-A, and beta A-P respectively. Fig. 6 shows the boxplots of p-values and Cohen-type effect sizes in red and green respectively in alpha band A-P. Other bands/directions showed similar results except for recruitment in beta band. Overall, across all bands the integration coefficient increased about 20% (16–32%). Fig. 5 shows the boxplots of medians of average percentage differences across subjects, for all electrodes, in alpha band A-P. Similar results were obtained for theta and beta bands in both P-A and A-P.

IV. Discussion

The direction of information flow has an impact on modularity and the A-P direction clearly carries information on the occurrence of microsleeps. Yue et al. [12] explain indicating how modularity is related to the complexity of the task at hand. The responsive state was associated with a simple 1-D tracking task, which might be why modularity is high and microsleeps come under a complex phenomenon which results in a decrease of modularity. The decrease in flexibility may reflect a loss in cognitive processing during microsleeps. The decrease in flexibility also suggests some resistance in changing modules. An increase in recruitment can be attributed to a high modular affinity of the electrodes. A decrease in the integration coefficient could imply that the complex communications between different parts of the brain are disrupted, resulting in decreased overall coordination of the brain. These collectively suggest a more segregated and disorganized but less integrated approach of the brain during microsleeps.

V. Conclusion

Changes in the mechanism of brain network before and during microsleeps were investigated to characterize the same using effective connectivity, obtained using surface EEG. From the results, it can be said that the cognitive learning of the brain is lowered, brain acts in a more partitioned manner, and also the overall coordination of the brain is lowered during microsleeps. These suggest a different way of wiring of the brain during microsleeps compared to the previous responsive states. More community based scalar measures are being analysed. Core-periphery topology based analysis is also being carried out. Apart from this other global graph measures are also being investigated. Also topological pattern based characterization using eigen-connectivity concept is under progress.

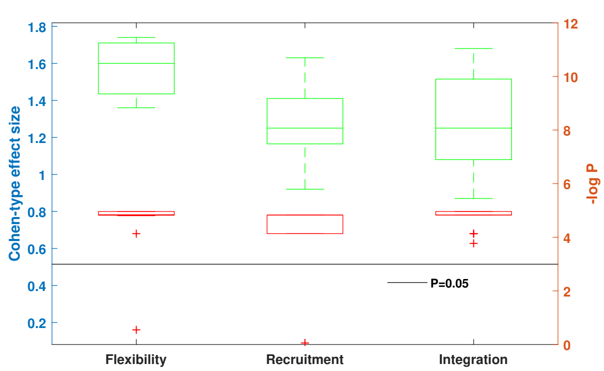

Fig. 6. Across-subjects analysis of flexibility, recruitment, and integration in alpha band, from anterior to posterior direction, green color representing the Cohen-type effect size and red color the p-values

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