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Analysis of brain activity based on long-term averaging of EEG signals.

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The bioelectrical activity of the brain is frequently measured using electroencephalography (EEG) or magnetoencephalography (MEG). Such signals may have a high sampling rate, with a resolution of more than a millisecond. On the other hand, functional magnetic resonance (fMRI) measures BOLD hemodynamic signals (blood-oxygen-level dependent) that provide information about metabolic demands with a resolution of about a single second. Both methods have their advantages and are used in the analysis of brain networks, diagnosis of mental disorders, neurofeedback, and other applications. It is hard to extract information relevant for diagnostic purposes from high-frequency noisy EEG multichannel data. Global EEG signals may be clustered in short time windows and assigned to a few templates called microstates. The whole EEG signal is then converted into a series of discrete labels of dominating microstates, preserving some information useful for clinical diagnostics (Michel, Koening, 2018). Both temporal and spatial resolution is thus greatly reduced, but the algorithm to compute microstates has several problems, as discussed by Shaw et al. (2019).

In our work we have investigated another simplification, sacrificing temporal information in favor of more precise spatial information. We perform a long-term temporal averaging of signals in each channel obtaining an asymptotic distribution of power that shows relative activations of different brain regions. We calculated Fourier spectra for time windows starting at each signal sample, obtaining average power for each electrode on the scalp. Resulting spatial maps are more complex than microstates, but we get only one map for each frequency band, while microstates provide a long series of labels corresponding to simpler maps. Interpretation is quite easy, showing hyper and hypoactive brain regions that can be linked to specific brain dysfunctions. These maps are relatively stable for each individual, and also show relative stability for whole groups of patients.

We have tested this method using EEG recordings of 45 adolescent boys (10-14 years old) with schizophrenia, described in Borisov et al. (2005). The control group of similar age consisted of 39 healthy schoolboys. EEG recordings were made in a wakeful, relaxed state with the eyes closed, using 16 electrodes placed in standard 10–20 system at O1, O2, P3, P4, Pz, T5, T6, C3, C4, Cz, T3, T4, F3, F4, F7, and F8. The sampling rate was 128 Hz, and only artifact-free EEG segments of the recordings were used for analysis. Such data is relatively low resolution and are easily measured in a clinical setting. The cumulative average power values and their variances were calculated separately for each electrode and the bands: delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), beta (12-30 Hz), gamma (30-60 Hz) as well as for the broadband spectrum (0.5-60 Hz).

Surprisingly, asymptotic power maps allowed for the classification of schizophrenia patients with accuracy comparable to sophisticated methods based on deep learning, and recurrence analysis. The classification was made using a linear SVM method implemented in a *Scikit-learn* Python library with the stratified 5-fold cross-validation. The average power for each channel and frequency band were normalized for each subject separately and used to create input feature vectors. For broadband calculations, we had only 16 features, while using all 5 bands delta-gamma we have 80 features. To exclude irrelevant features, we have used a recursive feature elimination technique (RFECV) with 10-fold cross-validation taken from the Scikit-learn function. In each step, it removes features based on the value of their SVM coefficients. The highest accuracy of 86.9±1.7% (87.5% correct for the norm, and 86.7% for the schizophrenia group) was obtained for the feature set based on all 5 bands reduced after RFECV to 42 dimensions.

Moreover, we can estimate which electrode and which frequency band contributes the most to the classification based on the maximum absolute values of the SVM weights. Starting with the most important combinations, the top 10 combinations are:

T4 α	F8 α	P3 β	C3 β	O2 α	Pz α	F8 θ	P4 θ	T4 θ	T3 θ

We have compared this result with a simple approach based on Convolutional Neural Network (CNN) by considering the data from each subject as an image, obtaining average accuracy of 79.8%±5.9%. To include some dynamics we have performed classification using Recurrence Quantification Analysis (RQA) features, using a pipeline from our previous work (Furman et al., 2022) that gave quite good results. For classification, we have used: the entropy of diagonal lines, trapping time, average diagonal line length, laminarity, determinism, longest vertical line length, the entropy of vertical lines, average white vertical line length, and entropy of white vertical lines. The final feature set was selected using the RFECV method. This method gave a classification accuracy of 82.2% for the set of 16 features after dimensionality reduction. Accuracy reported by Phang et al (2020) based on the time domain SVM results is slightly higher, 88%±3%. Calculations based on information about dynamics using only 3 transition probabilities between 4 microstates selected by RFECV is 78.5±2%. This shows that information about dynamics is also important.

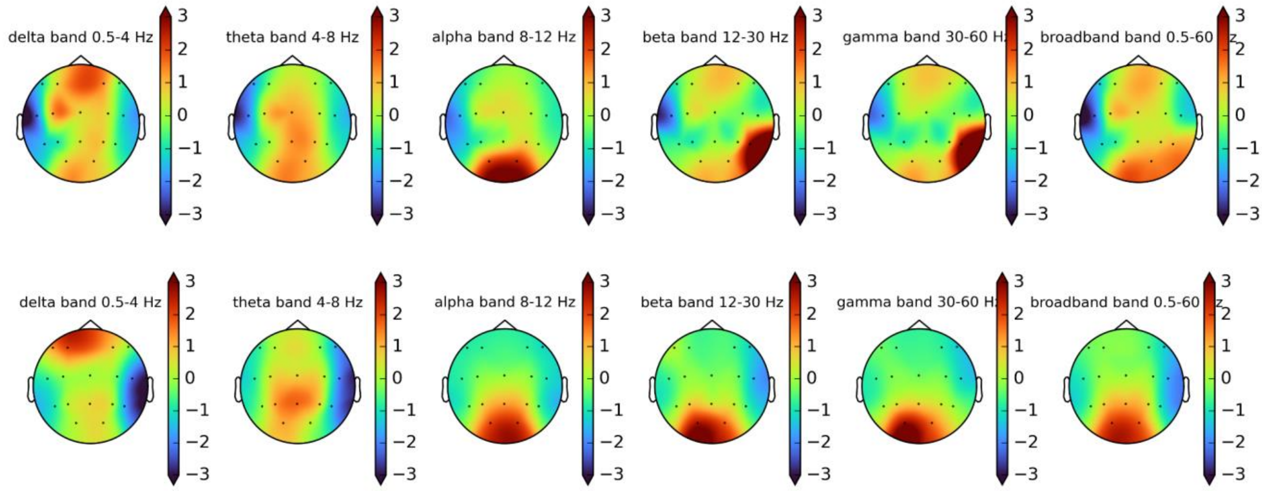

Fig. 1. Top row: a schizophrenic case (719-w1 sch) shows larger regions of high cortical activity. The control group case (27w1 norm, bottom row) shows lower activity in the right temporal lobe.

In conclusion, it is surprising that such simple approach gave remarkably good results. We will compare it using higher-density EEG data with more sophisticated methods in the near future.

References

Borisov SV, Kaplan A.Ya, Gorbachevskaya, NL, & Kozlova, I.A. (2005). Analysis of EEG Structural Synchrony in Adolescents with Schizophrenic Disorders. Human Physiology 31(3), 255

Furman, Ł., Duch, W., Minati, L., & Tołpa, K. (2023). Short-time Fourier transform and embedding method for recurrence quantification analysis of EEG time series. European Phys. J. Special Topics, 232, 135–149.

Michel CM & Koenig T. (2018). EEG microstates as a tool for studying the temporal dynamics of whole-brain neuronal networks: A review. NeuroImage, 180, 577–593.

Shaw, S. B., Dhindsa, K., Reilly, J. P., & Becker, S. (2019). Capturing the Forest but Missing the Trees: Microstates Inadequate for Characterizing Shorter-Scale EEG Dynamics. Neural Computation, 31, 2177

Phang, C.-R., Noman, F., Hussain, H., Ting, C.-M., & Ombao, H. (2020). A Multi-Domain Connectome Convolutional Neural Network for Identifying Schizophrenia From EEG Connectivity Patterns. IEEE Journal of Biomedical and Health Informatics, 24(5), 1333–1343.