

RESTING STATE BRAIN NETWORKS FROM EEG: HIDDEN MARKOV STATES VS CLASSICAL MICROSTATES

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MOTIVATION

- Temporal correlations in the power of spontaneous oscillatory activity of spatially distinct neuronal assemblies are a well established phenomenon described as **resting state brain networks** (RSNs).
- Here, we apply a hidden Markov Model (HMM) to the power envelope of EEG (Electroencephalography) signals, in order to identify quasi-stable topographies of correlated activation that the signal is likely to have emerged from.
- The aim of this study is to investigate the HMM's potential as an alternative or complementary method to classical EEG microstate analysis.

METHODS I – CLASSICAL EEG MICROSTATES

A commonly applied procedure to investigate the dynamics of global electric field configurations based on EEG recordings is known as **EEG microstates** [Koenig et al. 1999].

- The EEG signal is thought of as a sequence of a limited number of quasi-stable EEG topographies, each defining a microstate.
- Microstates are inferred based on the EEG topographies at local maxima of the global field power (GFP), which is given by the sum squared difference between all electrode potentials V_i and the mean potential \bar{V} .

$$GFP(t) = \sqrt{\frac{1}{n} \sum_i V_i(t) - \bar{V}(t)} \quad (1)$$

- Topographies at the GFP maxima are of particular interest because they feature the highest signal-to-noise ratio.
- The selected topographies are subject to clustering, in order to find states that reflect typical topographies.
- Classical microstate analysis usually limits itself to 4 clusters. Similar microstates have consistently been identified in a variety of studies.

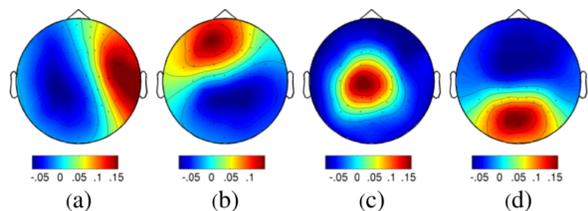


Figure 1: Classical EEG microstates, identified by k-means clustering

RESULTS I - CORRELATION BETWEEN METHODS

We compare the temporal and spatial properties of both microstates and HMM states.

- The most probable HMM state s_t at every time point is derived by the Viterbi algorithm.
- The relative time spent in each HMM states (microstate) is (a): 28% (24%), (b): 26% (25%), (c): 20% (21%), (d) 25% (29%).
- State time courses are derived with a GLM, and as such are partial correlations between the stable topographies and the signal time course.
- Pairwise correlations of the full time courses are shown in Fig. 3 and, unsurprisingly, exhibit a similar pattern as the spatial correlation structure in Fig. 4.

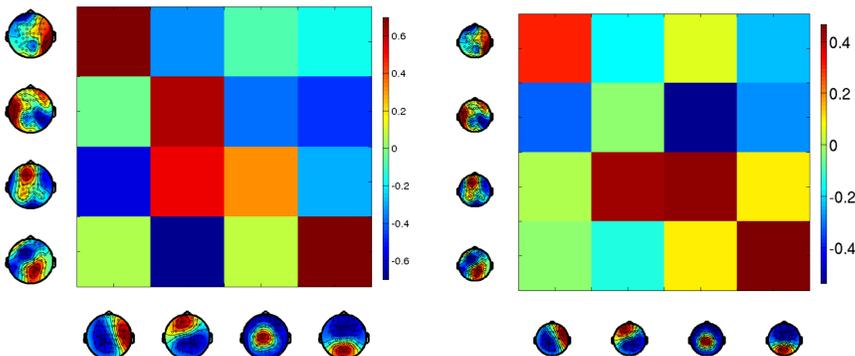


Figure 3: Correlation structure of microstate and HMM state spatial maps

- Notably, there are also clear differences:** We observe a strong spatial correlation between microstate (b) and HMM state (b), which is not reflected in the temporal correlation. Conversely microstate (c) and HMM state (d) feature a moderately positive time course correlation, while the spatial patterns are negatively correlated.
- The time courses provide information that can't be inferred from the spatial topographies alone. For instance, a comparison between HMM states (a) and (b) with microstate (c) shows a weak positive correlation in the first and a strongly negative correlation of the time courses in the latter.

RESULTS II - COMPARISON WITHIN METHODS

- A strong positive correlation between all EEG microstate time courses is visible (Fig. 5). Conversely, HMM state time courses are uncorrelated or negatively correlated (Fig. 6).

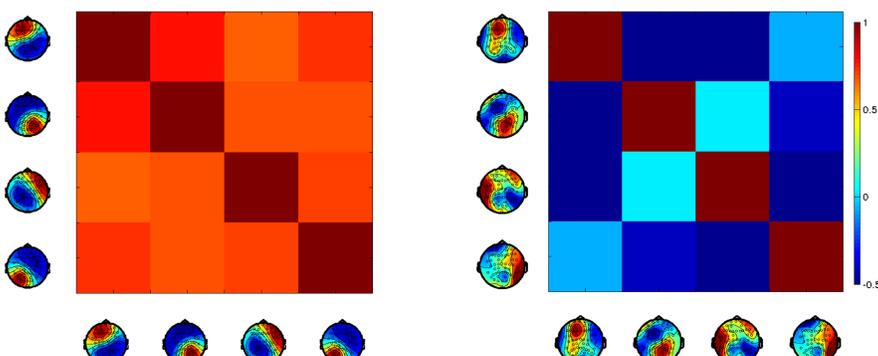


Figure 5: Microstate time course correlation

Figure 6: HMM state time course correlation

- Microstate time courses show strong pairwise temporal correlations, which is not observed for HMM states. We expect networks of different function to also be temporally distinct [Smith et al. 2012]. Hence, microstates are unlikely to be a good description of underlying physiology.

DATA ACQUISITION

- EEG data was acquired for **six healthy subjects**, with two sessions comprising ten minutes of data for each subject.
- Artifacts based on the cardiac signal, the eye blink signal and the signal's kurtosis and frequency spectrum were manually removed.
- The data was downsampled to 250 Hz, decomposed into 150 independent components, and band-pass filtered into the 1–40 Hz band.
- Power envelopes were calculated, downsampled to 42 Hz, demeaned, variance normalised and subsequently concatenated for a group level analysis.
- The concatenated envelopes were subject to a principal component analysis, retaining 20 components accounting for 95% of the variance.

METHODS II – HIDDEN MARKOV MODEL

In contrast to classical microstate analysis, the hidden Markov model that we propose is a generative model describing the observations that emerge from the rapid switching between quasi-stable topographies with a Gaussian observation model [Rezek and Roberts 2002; Baker et al. 2014].

- Model derivation:** At any given time t the system is in a state k , denoted s_t . Each state is associated with a Gaussian observation model. y_t denotes the vector of observation at time t .

$$P(y_t | s_t = k, \mu_k, \Sigma_k) \sim \mathcal{N}(\mu_k, \Sigma_k). \quad (2)$$

The transition probability between states is Markovian. The full posterior likelihood is given by:

$$P(y, s, \pi_0, \pi, \mu_k, \Sigma_k) = \prod_t P(y_t | s_t, \mu_k, \Sigma_k) P(s_t | s_{t-1}, \pi) P(\pi_t) P(\pi_0) P(\mu, \Sigma) \quad (3)$$

where the transition probabilities from state k to k' are described by $K \times K$ matrix π .

- The posterior is approximated using **variational Bayes** (assuming that the posterior factorises).
- We apply this model to the EEG power envelopes and derive the topographies, shown in Fig. 2.

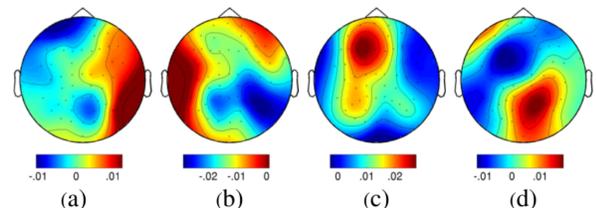


Figure 2: HMM based quasi-stable EEG topographies

RESULTS III - TIME SCALES OF NETWORK FLUCTUATIONS

To investigate the time scale of the inferred dynamics of state switching as supported by the envelope data, we correlate low pass filtered versions of each state time course with the envelope fluctuation of a representative EEG sensor. We vary the width of the low pass filter to find the time scale of highest correlation.

- We selected the sensor that had the highest correlation with the unfiltered state time course and repeated this analysis for every microstate and every HMM state varying the width of the filter.
- The results are shown in Fig. 7 and consistently exhibit maxima in the correlation at window width of 100–150 ms.
- None of the modalities shows a steadily higher correlation than the other.

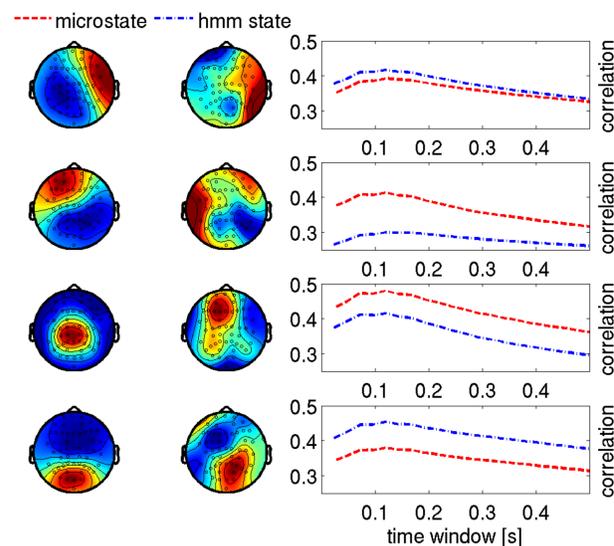


Figure 7: Time scale analysis of within-topography fluctuations – The dependency of the width of the averaging-window, applied to the state time course, on the correlation between the time course and the envelope of the most representative EEG sensor. We observe consistent maxima around 100–150 ms window widths.

CONCLUSION

- HMM state topographies are less spatially confined than classical microstates. Nevertheless, they feature spatially similar activation patterns that allow for a pairwise matching of states. This similarity is also present in the temporal evolution of the state time course.
- However, we find several **clear differences in the spatial and temporal properties** of the methods and the corresponding states. This indicates a dissimilarity between the methods that may correspond to a loss/gain of meaningful information.
- High temporal correlation between **microstates** casts **doubt on their suitability** to describe the underlying physiology.
- We find **dominating state lifetimes of 100–150 ms**, which is consistent with earlier findings.
- EEG HMM states could serve as a **physiologically motivated alternative to classical EEG microstates**.

REFERENCES

References

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