Using multivariate empirical mode decomposition to analyze broad-band EEG microstates

Matthew King-Hang Ma[1], Tan Lee[1], Manson Cheuk-Man Fong[2], William Shiyuan Wang[2]

CUHK Electronic Engineering

[1]Department of Electronic Engineering, The Chinese University of Hong Kong, Hong Kong; [2]Research Centre for Language, Cognition, and Neuroscience, The Hong Kong Polytechnic University, Hong Kong

Background and Motivation

- EEG microstates were described as a broad-band phenomenon but typically extracted from 2-20 Hz or 1-40 Hz band of interest. Several microstates were repeatedly observed in many previous studies.
- Although the microstate model allows any type of temporal dynamics behind a microstate as long as the dynamics remain stable, the common practice did not exploit this possibility.
- The aim of the study is to explore the EEG microstates phenomenon at different time scales to gain insights on the frequency composition of microstates.

The EEG Microstate Model

Resting-state, spontaneous EEG activity can be parsed into a limited number of scalp potential maps with different intensity at each time point as formulated:

$$Y = XA + E \tag{1}$$

where $Y \in \mathbb{R}^{n \times t}$ is the matrix of measured EEG signals, $X \in \mathbb{R}^{n \times k}$ is the matrix of potential maps, $A \in \mathbb{R}^{k \times t}$ is the activation/intensity matrix, $E \in \mathbb{R}^{n \times t}$ is the noise assumed to be IID and Gaussian. n, k, t are the number of channels, number of prototypical maps and number of time samples respectively.

The resultant maps were found to remain quasi-stable for around 60-120 ms before transiting to another map, and named microstates. 4 maps were repeatedly identified across many previous studies [1] (referred as "prototypical maps" afterwards):

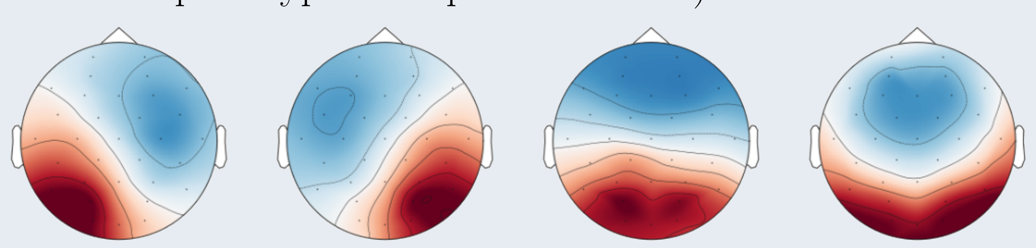


Figure 1: 4 prototypical maps. Left to right: Class A, B, C, D.

- Only one microstate is assumed to be active at a timepoint.
- Does not limit the frequency of underlying oscillators as long as they share similar dynamics.

Data and Methods

- 22 young [12F, age 20.7 (1.6)], 24 old [14F, age 72.3 (3.4)] subjects; native Cantonese speaker without known neurological disorders.
- 160 seconds of eyes-closed resting-state EEG.

Analysis flow:

1. Highpass-filtered at 1 Hz and eyes artifacts removal by ICA.
2. Decomposition of signals via noise-assisted multivariate empirical mode decomposition (NA-MEMD) [2].
3. Microstate segmentation at different time scales via adaptive k-means clustering algorithm [3]. Clustered maps were backfitted to the original signals to calculate the global explained variance (GEV).

Empirical Mode Decomposition

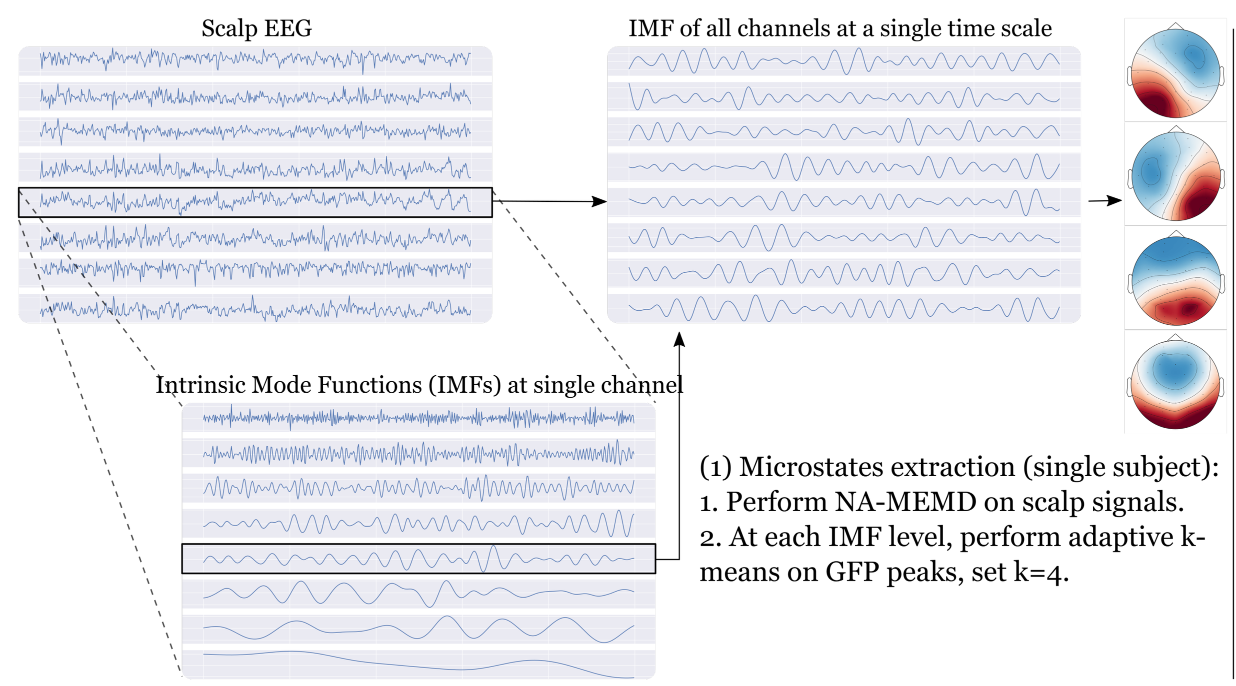
For a real signal $x(t)$, the univariate EMD finds a set of N intrinsic mode function (IMFs) $c_k(t)_{k=1}^{N}$ and a monotonic residue r:

$$x(t) = \sum_{k=1}^{N} c_k(t) + r \tag{2}$$

- The decomposition is completely data-driven and is designed for nonlinear, nonstationary signals such as EEG.
- The IMFs extracted are described as "monocomponent" that oscillate in a narrow range of frequency. One might understand the decomposition as a bandpass filter.
- In this study, the multivariate version NA-MEMD was employed.

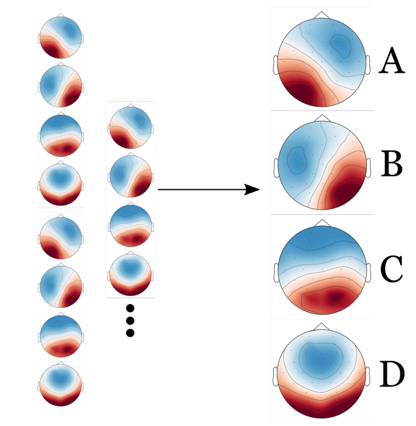
Microstate Analysis Flow

① Single Subject



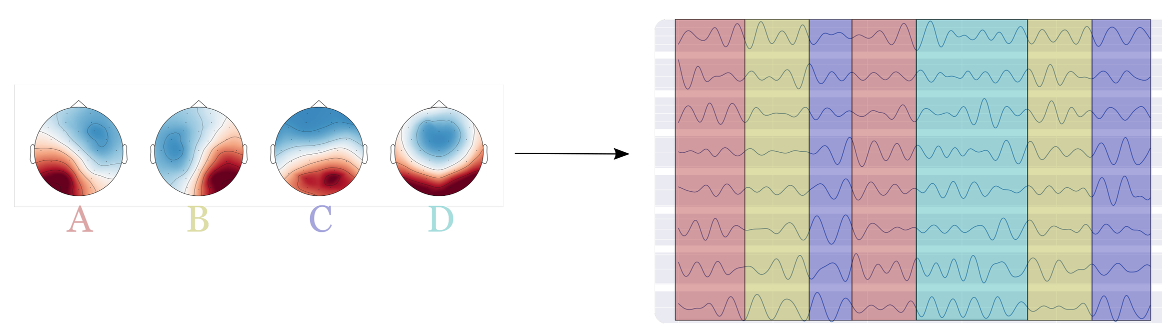
(1) Microstates extraction (single subject):
1. Perform NA-MEMD on scalp signals.
2. At each IMF level, perform adaptive k-means on GFP peaks, set k=4.

② Multiple Subjects



(2) Microstates extraction (multiple subjects):
1. Collect all individual microstates
2. Align similar maps and compute the 1st PC as the "averaged" map.
3. Repeat steps 2 for certain times and choose the trial that obtained highest average GEV across subjects.

③ Backfitting and calculate GEV



(3) Backfitting:
1. For each time point for each individual data, compute the distance between scalp EEG signals and grand averaged maps.
2. Assign the closest map to represent the original signal at that time point.
3. Represent whole signal just by the 4 maps.
4. Calculate the GEV.

Definition of Global Field Power (GFP) and Global Explained Variance (GEV):

$$\mathrm{GFP}_t = \sqrt{\frac{1}{n}\sum_{i=1}^{N} x_i^2} \qquad \mathrm{GEV} = \frac{\sum_{t=1}^{T}(\mathrm{GFP}_t \times \mathrm{Corr}_{x,y})^2}{\sum_{t=1}^{T}(\mathrm{GFP}_t)^2}$$

where x, y are the scalp maps and microstate maps at time point t. x_i refers to the value of x at channel i. Corr refers to the Pearson correlation.

Results - Microstates Maps extracted at different time scales

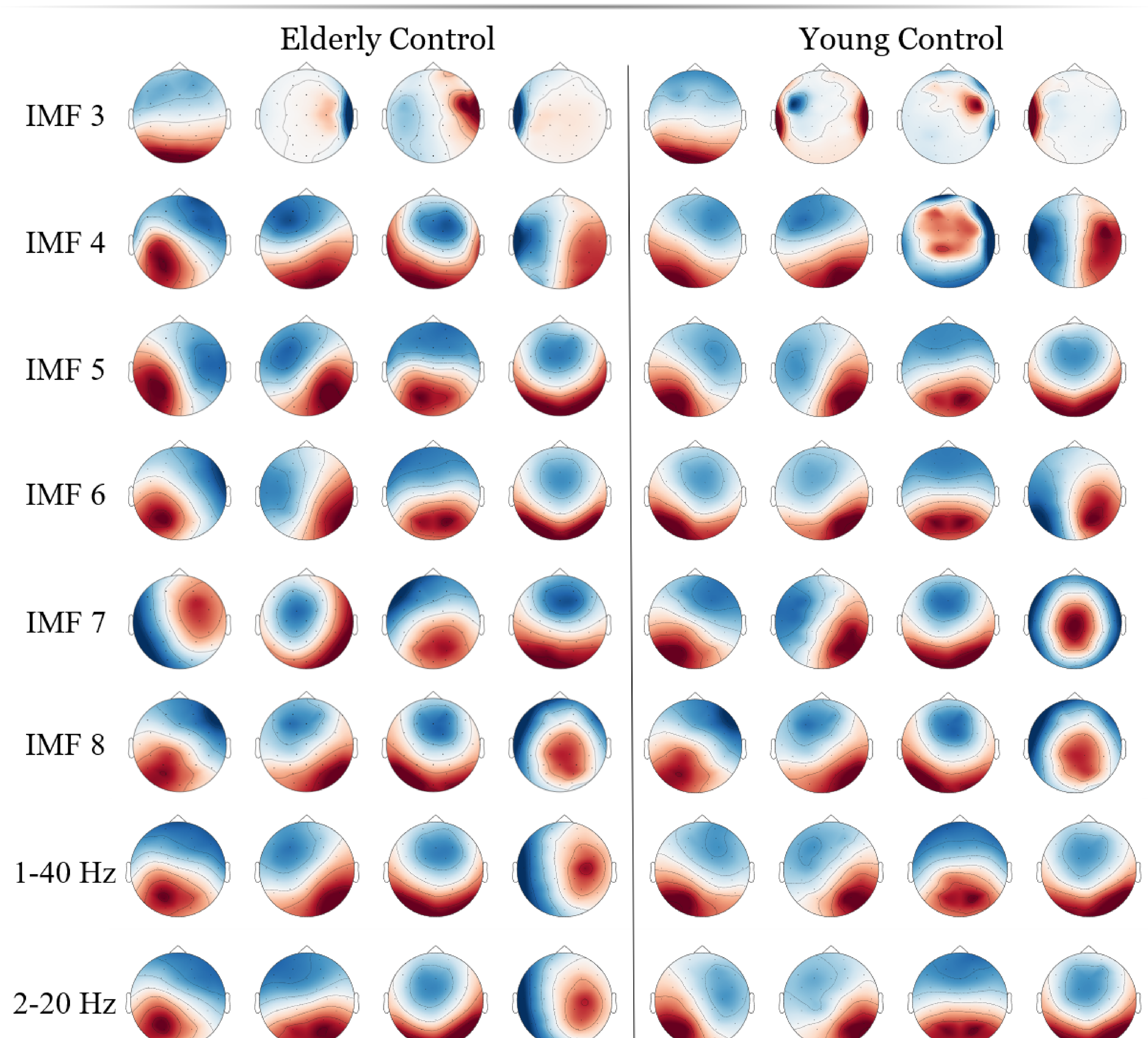


Figure 2: Microstates extracted using proposed and existing approaches.

Results and Discussion

Table 1: Summary table of microstates segmentation, (): uncertain categorization

	Elderly Control			Young Control		
Signal	Freq (Hz)	GEV (%)	Maps	Freq (Hz)	GEV (%)	Maps
IMF 1	169.43 (5.26)	36.52 (8.01)	(A),(B)	167.38 (5.38)	34.89 (7.47)	(A),(B)
IMF 2	95.50 (4.04)	36.14 (9.29)	NA	95.87 (7.80)	35.06 (9.66)	NA
IMF 3	53.09 (4.91)	33.13 (7.47)	(C)	53.30 (4.82)	31.24 (8.22)	(C)
IMF 4	29.03 (3.54)	41.69 (10.51)	A,B	29.89 (5.04)	39.50 (9.70)	A,B
IMF 5	16.70 (2.01)	54.37 (9.99)	A,B,C,D	17.11 (3.42)	59.89 (14.49)	A,B,C,D
IMF 6	9.33 (0.63)	61.51 (10.07)	A,B,C,D	9.82 (1.28)	64.79 (11.74)	A,B,C
IMF 7	4.80 (0.73)	47.25 (9.25)	A,B,C,D	5.30 (1.05)	50.21 (12.04)	A,B,D
IMF 8	2.46 (0.64)	39.74 (10.44)	A,B,D	2.92 (0.53)	43.55 (12.92)	A,B,D
1-40 Hz	NA	49.36 (9.65)	A,B,C	NA	51.97 (15.22)	A,B,C,D
2-20 Hz	NA	52.94 (10.01)	A,B,C	NA	55.71 (14.71)	A,B,C,D

- In common practice, microstate analyses were done using bandpass-filtered EEG from (1-40)/(2-20) Hz. Our results showed that the 4 prototypical maps might not share similar time scales, with some maps being more prevalent across multiple time scales and some being more frequency-specific.
- The GEV peaked at IMF6 (64.8%) and the value is higher than that from common practice, suggesting that EEG microstates are more stable in a particular time scale.
- The existing microstates extraction did not reproduce all 4 prototypical maps in elderly control. On the other hand, all 4 maps could be observed from IMF5 in both groups, suggesting that the present approach provided better localization of the prototypical maps.
- The presence of similar maps across both subject groups in IMF1/2 (not shown in figure) was interesting as typically only 1-50 Hz EEG was considered as informative. The underlying oscillators which generate the EEG signals could share the same dynamics in such a high frequency range.
- The reported GEV value is just barely comparable to many of the previous studies in which the GEV reported can be higher than 80%. This might showed that 4 maps were insufficient to account for the additional variances introduced by the expansion of the analysis to different time scales.

Associations between EEG microstates and resting-state networks

Several previous studies revealed the fMRI correlate of EEG microstates [1]:

A: Auditory network
B: Visual network
C: Saliency network
D: Attention network

Observations:

- A and B: observed together in both subject groups in a wider range of frequency (IMF 4-8).
- C and D: did not always show up; were seldom observed in both groups at the same time (only in IMF5).

The frequency-specific characteristics of the microstate maps could provide insights on the utilization of different oscillations within a particular network. With C and D more related to the cognitive domain, the expansion of microstates analysis to multiple time scales might offer a more detailed inspection of age-related changes.

Conclusion

- A data-driven decomposition technique was utilized to conduct microstate analyses on multiple time scales.
- The 4 prototypical maps may only reflect the dynamics of a particular time scale.
- The presence of common maps (other than prototypical maps) across groups in broad frequency range suggested different underlying dynamics in different frequencies.
- The EEG microstates might be described as "broad-band", but it should not be limited to the 4 overwhelmingly reported prototypical maps.

References

[1] C. M. Michel and T. Koenig, "EEG microstates as a tool for studying the temporal dynamics of whole-brain neuronal networks: A review," *NeuroImage*, vol. 180, pp. 577–593, Oct. 2018. [Online]. Available: https://doi.org/10.1016/j.neuroimage.2017.11.062

[2] N. ur Rehman and D. P. Mandic, "Filter bank property of multivariate empirical mode decomposition," *IEEE Transactions on Signal Processing*, vol. 59, no. 5, pp. 2421–2426, May 2011. [Online]. Available: https://doi.org/10.1109/tsp.2011.2106779

[3] R. D. Pascual-Marqui, C. M. Michel, and D. Lehmann, "Segmentation of brain electrical activity into microstates: model estimation and validation," *IEEE transactions on bio-medical engineering*, vol. 42, no. 7, pp. 658–665, Jul. 1995.

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Corresponding author: Matthew Ma (khma@link.cuhk.edu.hk)