POLARITY INVARIANT TRANSFORMATION FOR EEG MICROSTATES ANALYSIS

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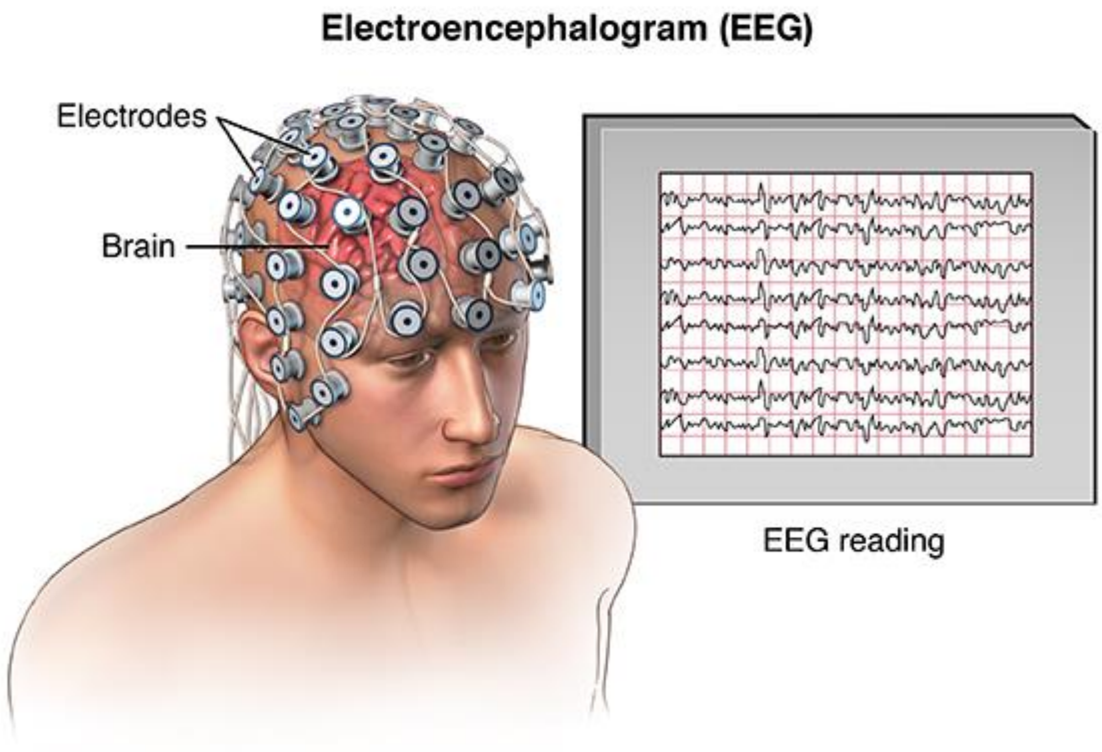
Agenda

- Introduction on EEG Microstates (EEG-ms)
- Elaboration on Extracting EEG-ms
- Polarity Invariant Transformation for EEG-ms
- Results
- Conclusion

Introduction

What is EEG?

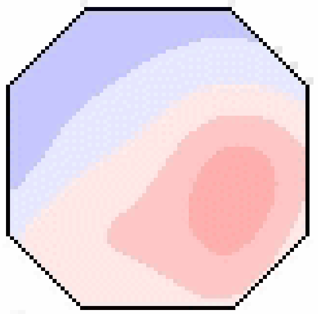


https://hvmn.com/biohacker-guide/cognition/eeg-measures-of-cognition

Introduction

EEG Microstates (EEG-ms)

- Brain goes into many local functional states can be said to be in one particular global functional state at each moment in time
- Brain experiences quasi-stability states that are followed by rapid changes over-time
- Brain states, if measured as EEG, are electric potential landscapes
- Electric potential landscapes generated by different distributions of neural electric activity in the brain, it is reasonable to assume that different microstates embody different functions of the brain



D Lehmann et al, Scholarpedia 4, 7632 (2011)

Introduction

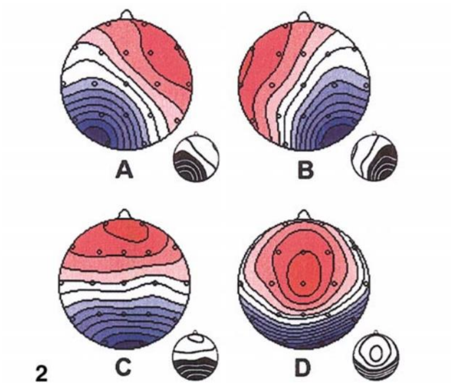
EEG-ms Analysis vs. Traditional EEG analysis

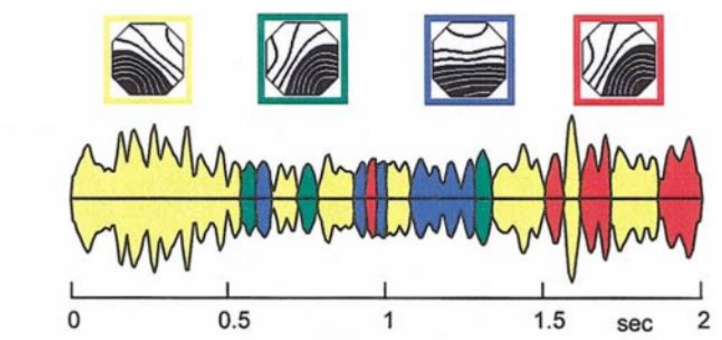
- Traditional Analysis:
  - EEG amplitude, power and phase modulation of EEG waveforms are local measures that vary with references
  - EEG amplitude and power vary at each time point, while phase varies at each electrode
- EEG-ms:
  - EEG-ms are reference-free global measurements
  - Stable for relatively long time (60-120 ms)
  - Reduces the complexity of EEG by looking number of topographies
  - Multichannel and broadband measure

Introduction

Canonical EEG-ms

- EEG-microstates in resting state
- *Koenig et al.2002∗* identified four microstate classes in the spontaneous EEG from 496 healthy subjects (6 to 80 year-olds)
- The mean duration of the microstates is 80-100 ms and varies with age
- Head seen from above, nose up; red positive, blue negative potential areas





T Koenig et al, Neuroimage 16, 41 (2002)

*T Koenig et al, Neuroimage 16, 41 (2002)

Methods: General Assumption of EEG

Mathematical Assumptions of EEG-ms

$$X_t = \sum_{i=1}^{K} a_{it} T_i + \epsilon_t$$

- X_t: EEG signal at time point t ($C \times 1$), with C is the number of channels
- K: the number of microstate
- a_{it} :intensity applied at each time point
- T_i: microstate ($C \times 1$), with C is the number of channels.
- ϵ_t: error term for time point t

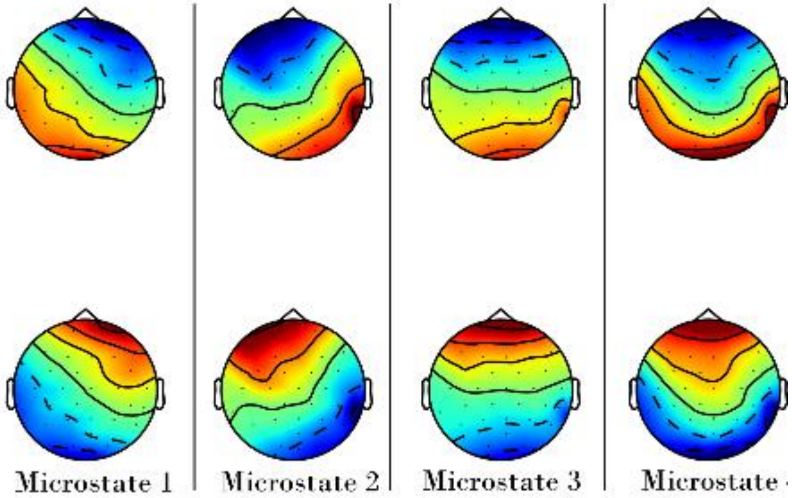
To allow for non-overlapping microstates at each time point t,all a_{it} must be zero except for one.

$$\begin{cases} a_{lt} a_{mt} = 0 \; \forall l \neq m \\ \displaystyle\sum_{i=1}^{K} a_{it}^2 > 0, \forall t \end{cases}$$

Methods: General Assumption of EEG

Polarity Invariant Property of EEG-ms

Same Microstates



$$x = \begin{bmatrix} x1 \\ \vdots \\ xp \end{bmatrix}$$

$$\bar{x} = -x = \begin{bmatrix} x1 \\ \vdots \\ xp \end{bmatrix}$$

Methods: Extracting EEG-ms

Extracting EEG-ms algorithm :

Step1: Set K, X

Step 2: Initialize K random MSs

$$T_i \quad with \;\; i = 1..K$$

Step 3:Normalizing EEG MSs such that:

$$\|T_i\| = 1 \;\text{ and }\; (T_i'T_j)^2 < 1 \; for \; i \neq j$$

Step 4: Assign labels

$$L_{M\times 1} = argmax\{(X'T)^2\}$$

Step 5: Update MSs Templates

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For i=1..K

a. $S_i = X_i X_i'$ with X_i EEG points that belongs to MS i

b. $T_i = argmax_{X_t} \{X'_t S_i X_t\}$

Step 6: Calculate the explained variance

$$\sigma_D^2 = (\sum_{i=1}^{M}(X'_i X_i)^2)/(K(M-1))$$

$$\sigma_u^2 = \sigma_D^2 - (\sum_{i=1}^{M}(T_i' X_i)^2)\,/(K(M-1))$$

$$R^2 = 1 - \sigma_u^2/\sigma_D^2$$

Step 7: Repeat step 4 through step 7 until R^2 is large enough

Methods: Polarity Invariant Transformation

Motivation

1. EEG-ms is a polarity invariant analysis, and thus it requires special handling for identifying the microstates
2. Thus, transforming the EEG time points into a new space will alleviate the challenges of handling the polarity of EEG
3. Also, it allows using general clustering algorithms to identify microstate templates
4. All results are compared to two commonly used algorithms modified-k-mean and AAHC*

*C. M. Michel and T Koenig, *NeuroImage 188, 577 (2017)*

Methods: Polarity Invariant Transformation

Suggested Solution

1. The transformation of EEG signals is achieved by mean of kernel concept
2. While there are many types of kernels, to best of our knowledge, the literature does not provide a kernel with polarity invariant property
3. Thus, we provide here our derivation for the proposed kernel. The kernel is deployed using Kernel-PCA (KPCA) paradigm*
4. With kernel transformation, the data are transformed using non-linear and polarity invariant kernel into a new space such that EEG points that represent similar EEG microstates will become closer to each other, while points that belong to different EEG microstates will spread out

*F. von Wegner et al, Neuroimage 158, 99 (2017)

Methods: Polarity Invariant Transformation

Polarity Invariant Kernel PCA

- EEG signals $\boldsymbol{X}$ with $\boldsymbol{n}$ time points such that $\boldsymbol{X} = \{\boldsymbol{x_i}\}$ with $\boldsymbol{i} = \mathbf{1}, \ldots, \boldsymbol{n}$ and $\boldsymbol{x_i}$ is an $\boldsymbol{p}$ dimensional vector corresponding to the number of channels in EEG.

$$\frac{1}{n}\sum_{i=1}^{n}\Phi(x_i) = 0 \qquad (\mathbf{Eq.\,3.1})$$

$$C = \frac{1}{n}\sum_{i=1}^{n}\Phi(x_i)\,\Phi(x_i)^T \qquad (\mathbf{Eq.\,3.2})$$

$$Cv_k = \lambda_k v_k \qquad (\mathbf{Eq.\,3.3})$$

$$Cv_k = \frac{1}{n}\sum_{i=1}^{n}\Phi(x_i)\,\Phi(x_i)^T v_k = \lambda_k v_k \qquad (\mathbf{Eq.\,3.4})$$

$$v_k = \sum_{i=1}^{n} a_i\ \Phi(x_i) \qquad (\mathbf{Eq.\,3.5})$$

$$Cv_k = \frac{1}{N}\sum_{i=1}^{n}\Phi(x_i)\,\Phi(x_i)^T\sum_{j=1}^{n} a_i\ \Phi(x_j) = \lambda_k\sum_{i=1}^{n} a_i\ \Phi(x_i) \qquad (\mathbf{Eq.\,3.6})$$

Methods: Polarity Invariant Transformation

Polarity Invariant Kernel PCA, cont'd,

$$\mathcal{K}(x_i, x_j) = \Phi(x_i)\Phi(x_j)^T \qquad (\textbf{Eq. 3.7})$$

$$\frac{1}{N}\mathcal{K}(x_i, x_j)\sum_{j=1}^{n} a_i\ \mathcal{K}(x_i, x_j) = \lambda_k \sum_{i=1}^{n} a_i\ \mathcal{K}(x_i, x_j) \qquad (\textbf{Eq. 3.8})$$

$$\mathrm{K}^2\alpha = \lambda_k N \mathrm{K}\alpha \qquad (\textbf{Eq. 3.9})$$

$$y_k(x) = \Phi(x)^T v_k = \sum_{i=1}^{n} a_i\,\mathcal{K}(x, x_j) \qquad (\textbf{Eq. 3.10})$$

$$\widetilde{\mathrm{K}} = \mathrm{K} - 1_n\mathrm{K} - \mathrm{K}1_n + 1_n\mathrm{K}1_n \qquad (\textbf{Eq. 3.11})$$

Methods: Polarity Invariant Transformation

A kernel with polarity invariant derivation

$$x = \begin{bmatrix} x1 \\ \vdots \\ xp \end{bmatrix}$$

$$\mathcal{K}(x, y) = \mathcal{K}(x, -y) \qquad (\textbf{Eq. 3.12})$$

We rely on using a gaussian kernel with Euclidean distance.

$$\mathcal{K}(x, y) = \exp\big(-\gamma d(x, y)\big)$$

$$y = \begin{bmatrix} y1 \\ \vdots \\ yp \end{bmatrix}$$

But we need a distance function such that:

$$d(x, y) = d(x, -y) \qquad (\textbf{Eq. 3.13})$$

One suggestion is :

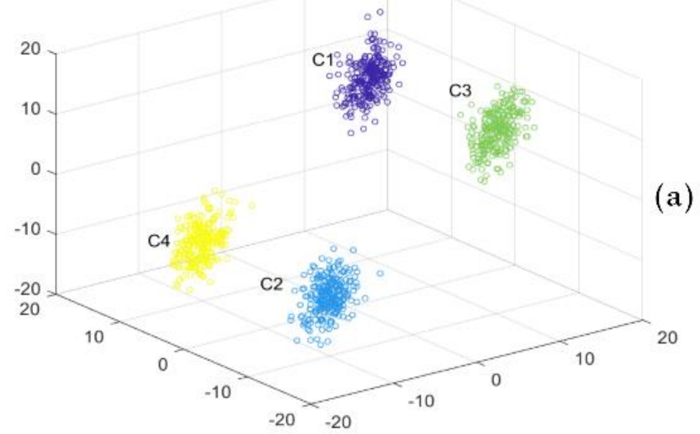
$$D(x, y) = \min[d(x, y), d(x, -y)] \qquad (\textbf{Eq. 3.14})$$

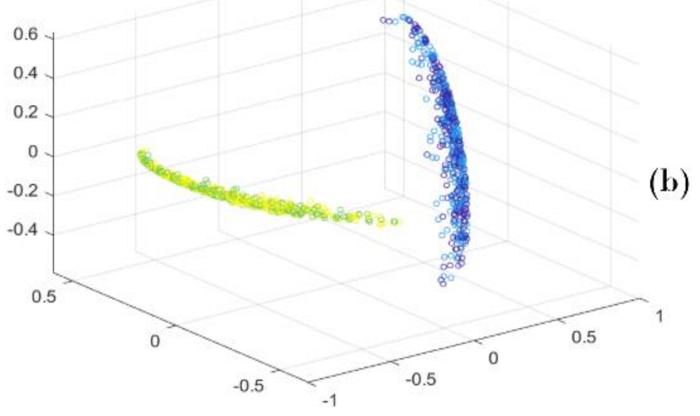
$$D(x, y) = \min[\|x - y\|^2, \|x + y\|^2] \qquad (\textbf{Eq. 3.15})$$

$$= \min[-2x1y1 - 2x2y2 - \cdots - 2xpyp,$$

Results: Polarity Invariant Transformation

Demo for the transformation in 3D

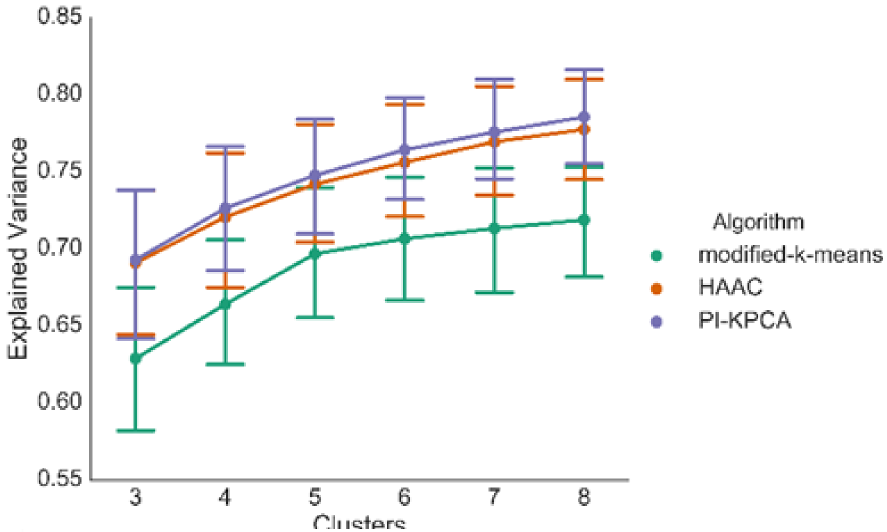




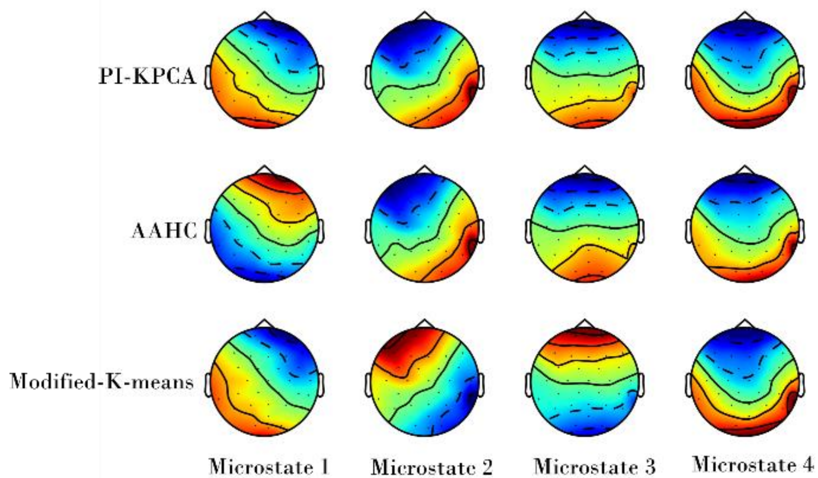
Results: Polarity Invariant Transformation

Results

Explained Variance Comparison from 10 healthy resting-state EEG (8 min)



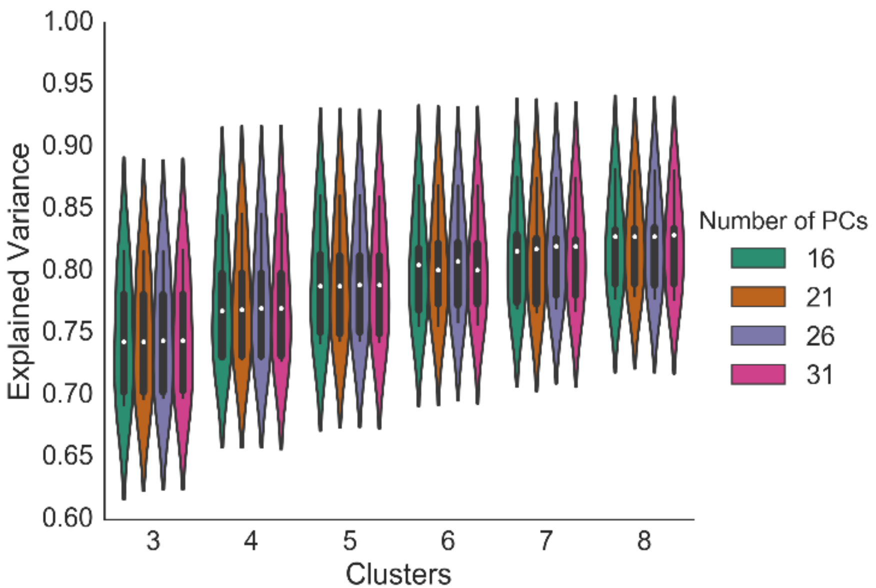
Topography Comparison



Results: Polarity Invariant Transformation

Results

The effect of the number of PCs



Execution time

Algorithm	Execution time per subject (sec)
Modified-K-means	7
AAHC	23.3
PI-KPCA	**3.3**

Conclusion

- We have introduced a new transformation to identify the EEG Microstates by applying a nonlinear transformation with polarity invariant property
- The transformation relies on KPCA with a particular
- We have also demonstrated in our demo example how the transformation works using a synthetic data in 3D dimension
- Our testing has shown that the proposed that transformation work very well and can improve upon the most common EEG Microstates algorithms namely, modified-k-means and HAAC
- It can be shown that from the figure that PI-KPCA based algorithm always outperform other algorithms
- The topographies of the extracted microstates from AAHC and modified-k-means are highly similar and indicates that the identified microstates are similar to each other

Questions ?

References

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Supplementary (1)

Global Field Power (GFP) Extraction Steps:

1. Average Reference data
2. Calculate GFP:

$$GPF = \sqrt{\frac{\sum_{i=1}^{n}(\ x_i(t) - \bar{x}(t))^2}{n}}$$

- With $x_i(t)$ is electrode voltage value at time point t and $\bar{x}(t)$ is mean of electrodes voltages at that time point

3. Peak detection

- We select randomly n Maps (for later we call it K)

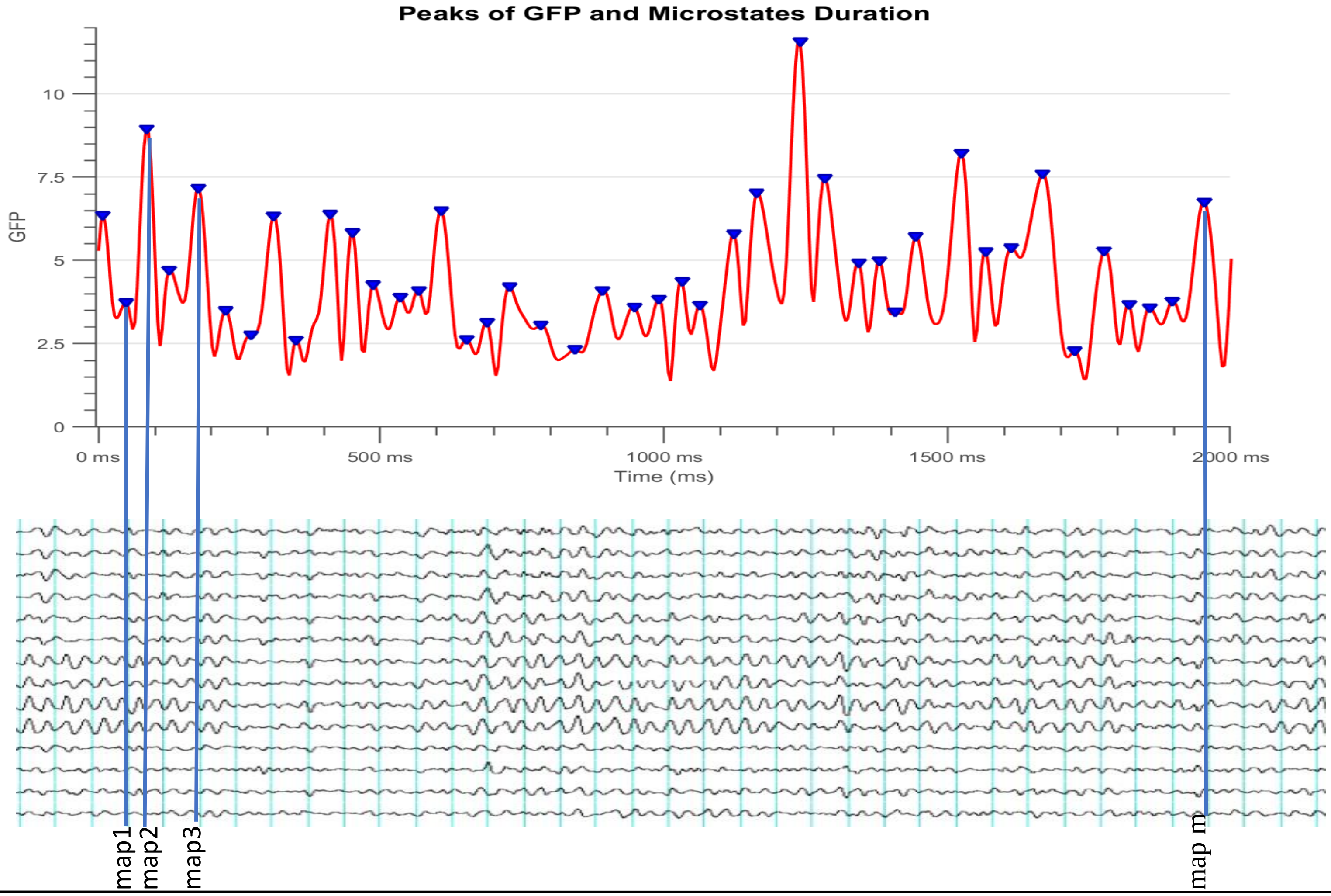
4. Store electrodes information at each peak

   - We call it X such that $X = C \times M$

Repeat this for individual subjects

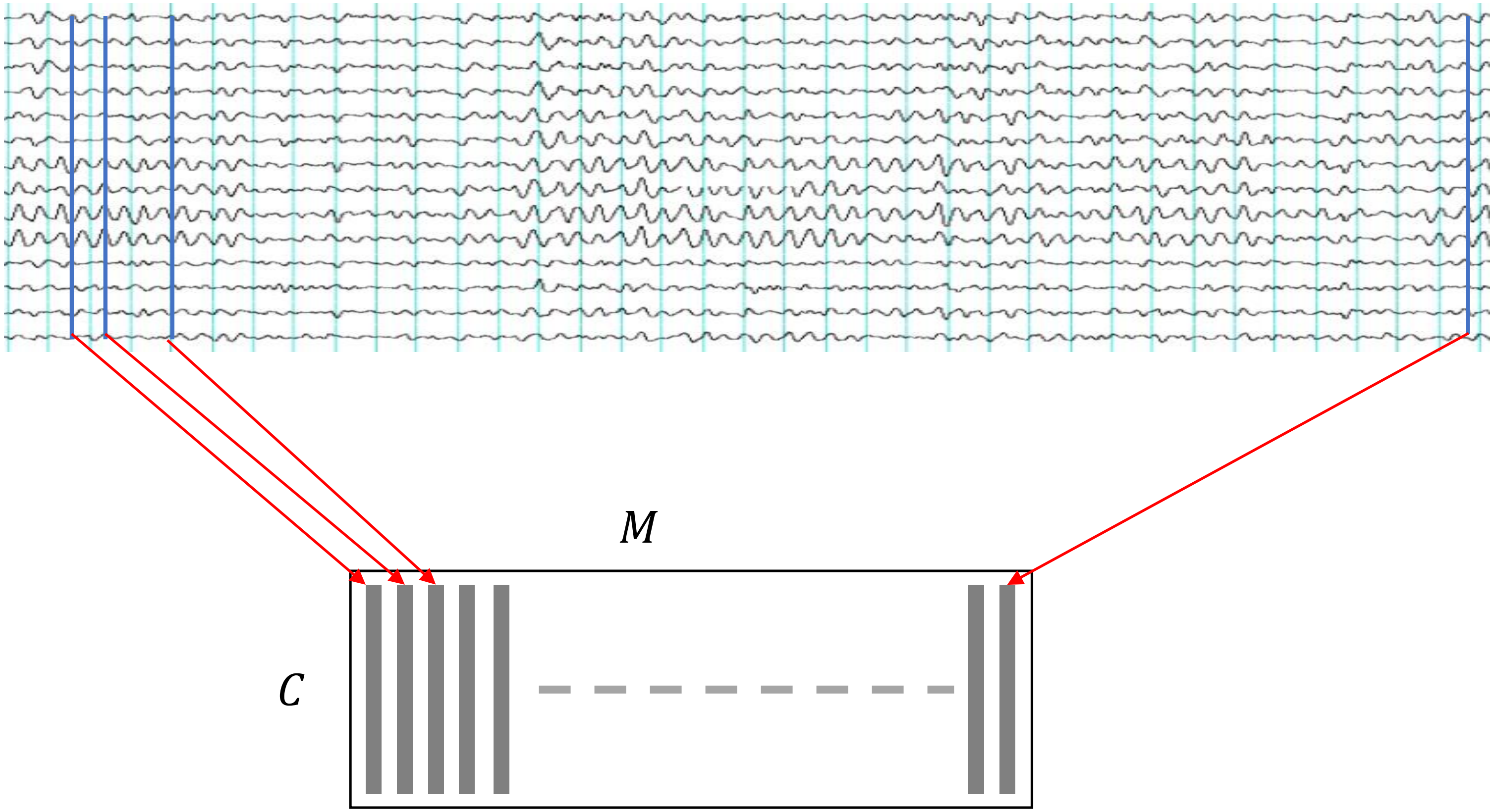
Supplementary (2)

GPF Peak Detection



Supplementary (3)

Data organizing for the algorithm



X

Algorithm 1:

Step1: Set K, X

Step 2: Initialize K random MSs

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$$X = C \times M$$

$$T = C \times K$$

Supplementary (5)

Algorithm 1: cont'd

Only positive terms !

$$X = C \times M$$
$$T = C \times K$$

Step 4: Assign labels

$$L_{M\times 1} = argmax\{(X'T)^2\}$$

Step 5: Update MSs Templates

For i=1..K

a. $S_i = X_i X_i'$ with X_i EEG points that belongs to MS i

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Step 6: Calculate the explained variance

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$$\sigma_u^2 = \sigma_D^2 - (\sum_{i=1}^{M} (T_i' X_i)^2)\ /(K(M-1))$$
$$R^2 = 1 - \sigma_u^2/\sigma_D^2$$

Step 7: Repeat step 4 through step 7 until R^2 is large enough

Example of assigning labels (K=4)

3	0.55	0.6	0.7	0.15
1	0.89	0.3	0.8	0.33
4	0.54	0.69	0.49	0.96
3	0.57	0.33	0.95	0.66
⋮	⋮	⋮	⋮	⋮
2	0.1	0.89	0.75	0.05

Repeat this for individual subjects !!!

Supplementary (6)

Output of the previous steps:

MSs for Subj 1

MSs for Subj 2