Common Spatial Pattern: Application on the Identification of Brain Regions Involved in Epilepsy

Samareh Samadi

Directors:

Christian JUTTEN

Hamid SOLTANIAN-ZADEH

GIPSA-lab, Université de Grenoble, Grenoble, France

Control and Intelligent Processing Center of Excellence (CIPCE)
School of Electrical and Computer Engineering, University of Tehran, Tehran, Iran

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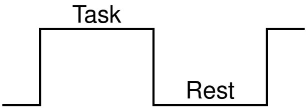
Table of contents

Motivation and Goals

Motivation Discrimination between two brain states.



Goal Extraction of sources related to a specific state or event by decreasing the effect of unrelated sources like background activity, noise, etc.

Motivation and Goals

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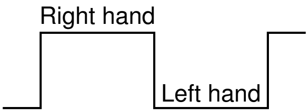

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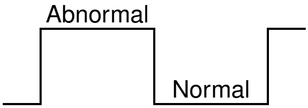

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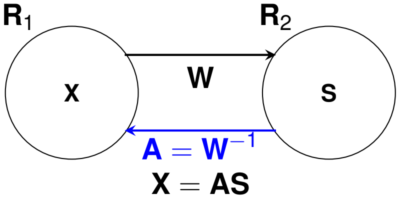
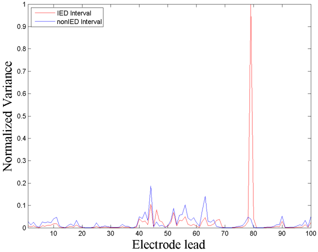
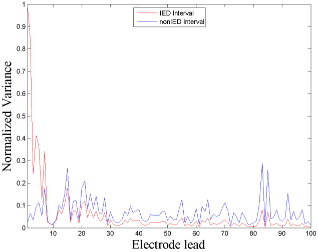
Review

- First proposed by Fukunaga and Koontz in 1970.
- Introduced in the field of EEG analysis by Koles et al. in 1990.
- Multidimensional observations (e.g. electrodes in EEG)
- Applications
  - Brain Computer Interface (BCI)
  - Identification of abnormal EEG patterns
- CSP computes linear combination of observations which maximizes the variance difference between the two classes.

Review


R1
R2
X
W
S
A = W^{-1}
X = AS


IED Interval
nonIED Interval
Normalized Variance
Electrode lead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Review

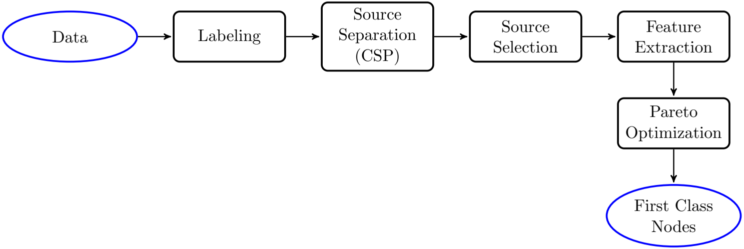
$$\max_{\mathbf{W}} \frac{\mathbf{W}^T \widehat{\mathbf{R}}^1 \mathbf{W}}{\mathbf{W}^T \widehat{\mathbf{R}}^2 \mathbf{W}} \; s.t. \; \|\mathbf{W}\| = 1$$

$$\mathit{Rayleigh - Ritz \ Theorem} \Downarrow$$

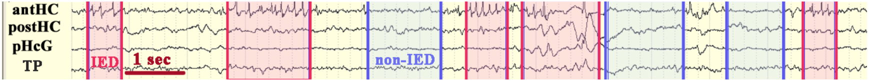
$$GEVD(\widehat{\mathbf{R}}^1, \widehat{\mathbf{R}}^2) : \widehat{\mathbf{R}}^1 \mathbf{W} = \widehat{\mathbf{R}}^2 \mathbf{W} \Lambda$$

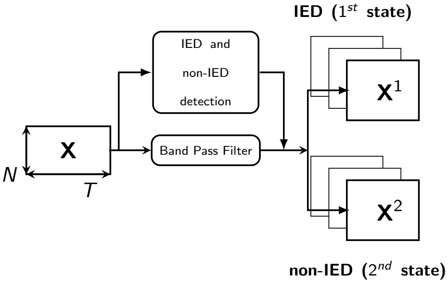
- Λ : the diagonal matrix of eigenvalues.
- The eigenvalues are ranked in decreasing order i.e. according to extracted source similarity with the 1^{st} class time courses.
- CSP relates with source separation based on non-stationarity of sources (see Pham and Cardoso, 2001).

Method

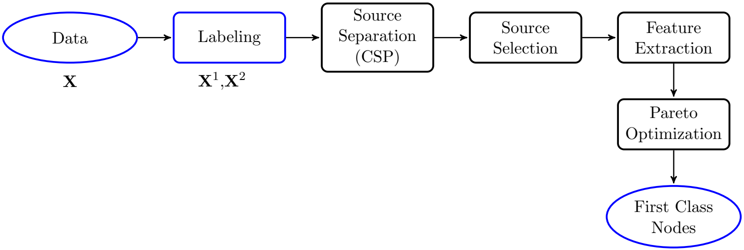

Data
Labeling
Source Separation (CSP)
Source Selection
Feature Extraction
Pareto Optimization
First Class Nodes

Data Segmentation

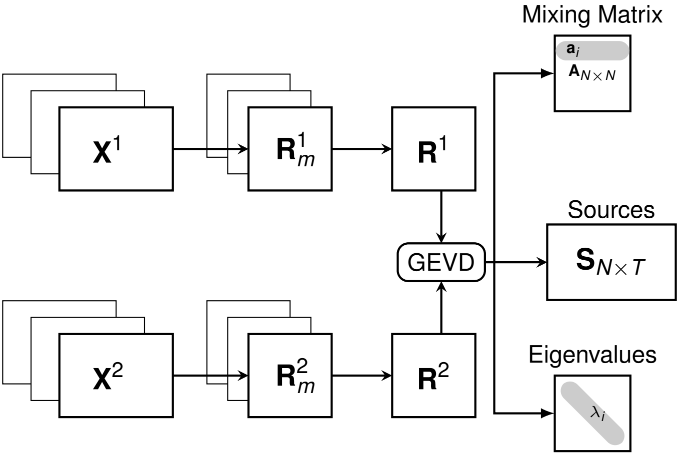




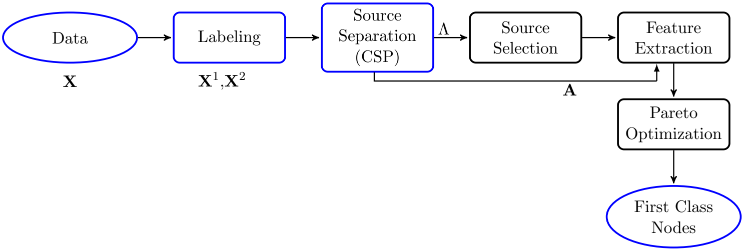
Labeling Results



Common Spatial Pattern (CSP)



CSP Results


Data
X
Labeling
X1,X2
Source Separation (CSP)
Λ
A
Source Selection
Feature Extraction
Pareto Optimization
First Class Nodes

Source Selection

- Eigenvalues can be used as a measure of the relevancy of the sources to the first class.

$$\lambda_1 > \lambda_2 > \cdots \lambda_{i^*} > \cdots > \lambda_N$$

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- Interpret λ_i as a membership probability.

$$p(\mathbf{s}_i \in \omega_1) = \frac{\lambda_i}{\sum_j \lambda_j}$$

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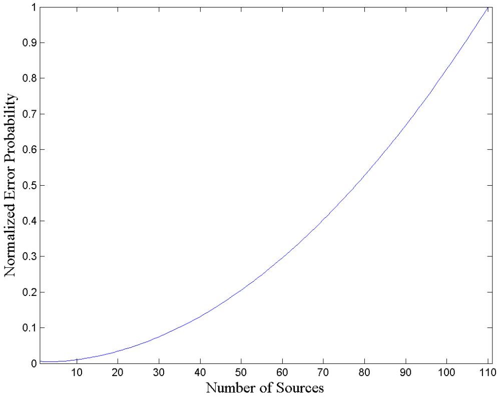

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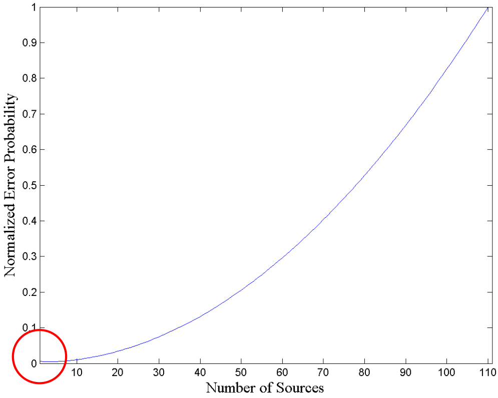

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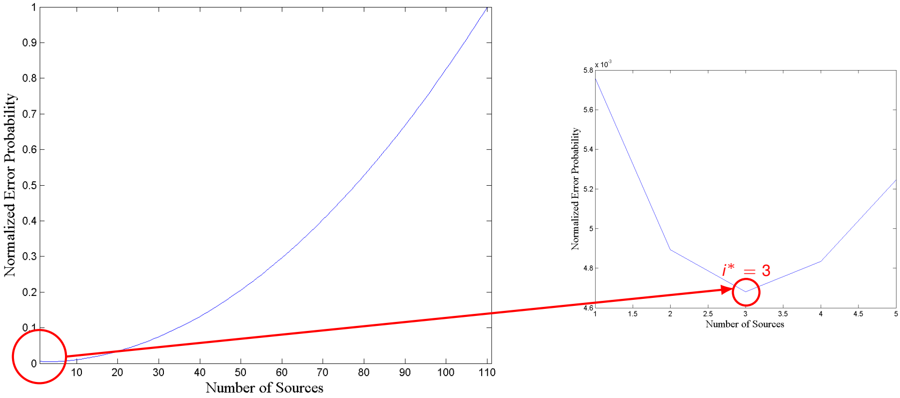

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$$\lambda_1 > \lambda_2 > \cdots \lambda_{i^*} > \cdots > \lambda_N$$

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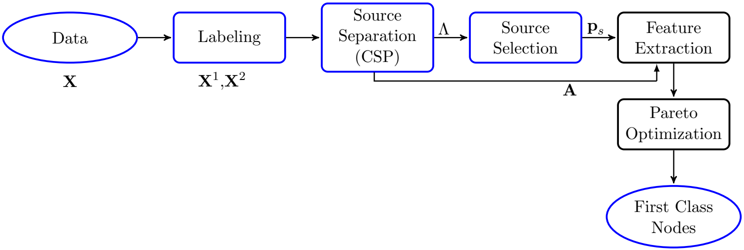
- Interpret λ_i as a membership probability.

$$p(\mathbf{s}_i \in \omega_1) = \frac{\lambda_i}{\sum_j \lambda_j}$$

- Choose i^* which minimizes the overall probability of error.
- $$\mathbf{p}_s(i) = p(\mathbf{s}_i \in \omega_1) = \begin{cases} \frac{\lambda_i}{\sum_j \lambda_j} & i = 1, \cdots, i^* \\ 0 & i = i^* + 1, \cdots, N \end{cases}$$

Source Selection

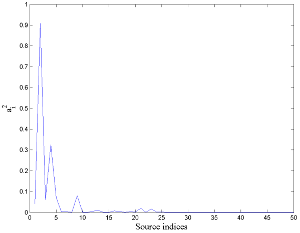


Feature Extraction

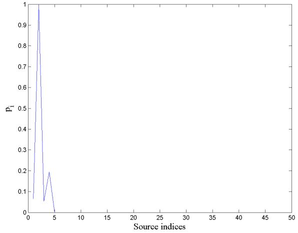
- The relevant probability of each node (electrode lead) to the first class (IED regions) via each sources can be defined as:

$$p(\mathbf{x}_i \,|\mathbf{s}_j\,) = \frac{a_{ij}^2}{\sum_{j=1}^{N} a_{ij}^2}$$

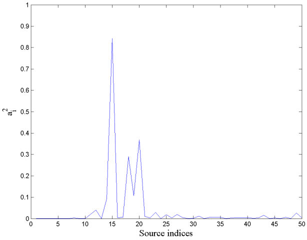
Using the mixing model $\mathbf{x}_i = \sum_{j=1}^{N} a_{ij}\mathbf{s}_j$.



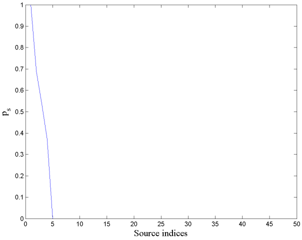
$$\mathbf{p}_i = \left[p(\mathbf{x}_i \,|\mathbf{s}_j\,)p(\mathbf{s}_j \in \omega_1)\right]$$



Feature Extraction

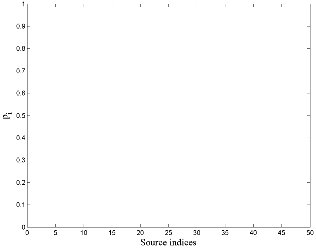


$\times$



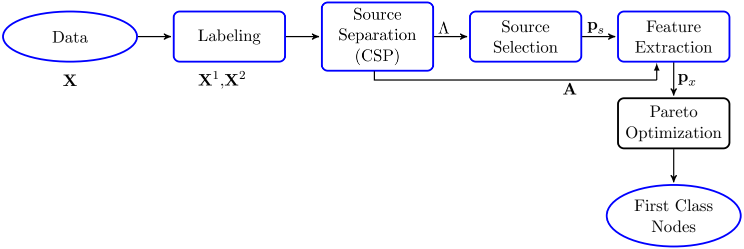
$$p(\mathbf{x}_i \,|\, \mathbf{s}_j) = \frac{a_{ij}^2}{\sum_{j=1}^{N} a_{ij}^2}$$

$$p(\mathbf{s}_i \in \omega_1) = \begin{cases} \frac{\lambda_i}{\sum_j \lambda_j} & i = 1, \cdots, i^* \\ 0 & i = i^* + 1, \cdots, N \end{cases}$$

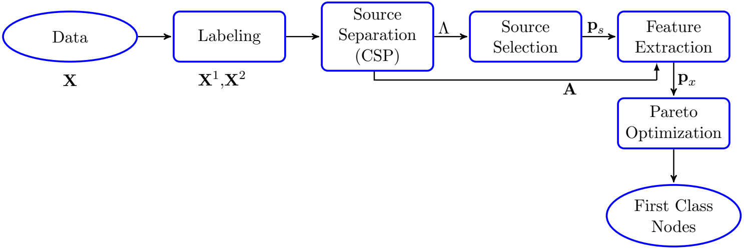


$$\mathbf{p}_i = \left[p(\mathbf{x}_i \,|\, \mathbf{s}_j) p(\mathbf{s}_j \in \omega_1) \right]$$

Feature Extraction



Pareto Optimization



Pareto Optimization Results

P1	antHC	postHC	amyg	pHcG	mTP	f'11
visually inspected SOZ	×	×	×	×	×	
DCG	×		×	×		
CSP	×	×	×	×	×	×
P2	antHC	postHC	amyg	pHcG		
visually inspected SOZ	×	×	×	×		
DCG	×					
CSP	×					
P3	antHC	postHC	pHcG			
visually inspected SOZ	×	×	×			
DCG	×	×				
CSP	×	×	×			
P4	antHC	postHC	amyg	entCx	mTP	
visually inspected SOZ	×	×	×	×	×	
DCG	×	×	×	×		
CSP	×	×				
P5	midInsG					
visually inspected SOZ	×					
DCG	×					
CSP	×					

amyg: amygdala; ant/post/m: anterior/posterior/mesial; CG: cingulate gyrus; entCx: entorhinal cortex; HC: hippocampus; Ins: insula; midInsG: middle short gyrus of insula; pHcG: parahippocampal gyrus; TP: temporal pole;

Pareto Optimization Results

P1	antHC	postHC	amyg	pHcG	mTP	f'11
visually inspected SOZ	×	×	×	×	×	
DCG	×		×	×		
CSP	×	×	×	×	×	×
P2	antHC	postHC	amyg	pHcG		
visually inspected SOZ	×	×	×	×		
DCG	×					
CSP	×					
P3	antHC	postHC	pHcG			
visually inspected SOZ	×	×	×			
DCG	×	×				
CSP	×	×	×			
P4	antHC	postHC	amyg	entCx	mTP	
visually inspected SOZ	×	×	×	×	×	
DCG	×	×	×	×		
CSP	×	×				
P5	midInsG					
visually inspected SOZ	×					
DCG	×					
CSP	×					

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visually inspected SOZ	×	×	×	×	×	
DCG	×		×	×		
CSP	×	×	×	×	×	×
P2	antHC	postHC	amyg	pHcG		
visually inspected SOZ	×	×	×	×		
DCG	×					
CSP	×					
P3	antHC	postHC	pHcG			
visually inspected SOZ	×	×	×			
DCG	×	×				
CSP	×	×	×			
P4	antHC	postHC	amyg	entCx	mTP	
visually inspected SOZ	×	×	⊗	⊗	⊗	
DCG	×	×	×	×		
CSP	×	×				
P5	midInsG					
visually inspected SOZ	×					
DCG	×					
CSP	×					

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Comparison Results

	Precision		Sensitivity	
	CSP	DCG	CSP	DCG
p1	83.3	100	100	60
p2	100	100	25	25
p3	100	100	100	67
p4	100	100	40	80
p5	100	100	100	100
mean	96.6	100	73	66.4

Conclusion

- Basically, this method is well suited for separating the discriminative sources between two brain states: here, IED and non-IED.
- The CSP method is fast and simple.
- The method is robust provided that covariance matrices are accurately estimated.
- The estimated IED regions are congruent with the visually inspected SOZ by the epileptologist.
- Future work: automatic detection of IED and non-IED time intervals.