STATIONARY COMMON SPATIAL PATTERNS: TOWARDS ROBUST CLASSIFICATION OF NON-STATIONARY EEG SIGNALS

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Introduction

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  $\Rightarrow$ Use spatial filtering method e.g. Common Spatial Pattern (CSP) to reduce dimensionality and increase signal-to-noise ratio.
- Problem: CSP does not tackle the non-stationarity issue.
  $\Rightarrow$ We propose an extension called stationary CSP (sCSP) which extracts stationary features.

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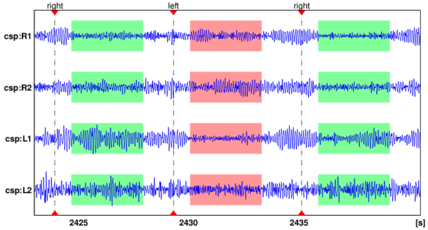
$\Rightarrow$ Extraction of invariant features and adaptation to changes are key challenges in BCI research.

Methods

Common Spatial Patterns

- CSP maximizes the variance of bandpass filtered EEG signals from one class while minimizing the variance from the other class.



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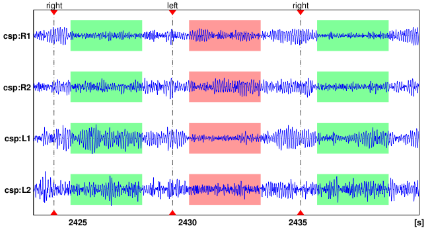

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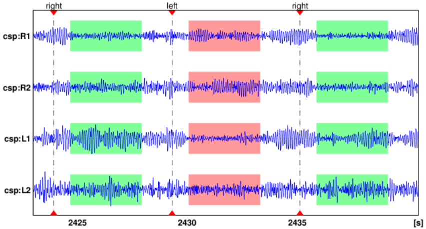

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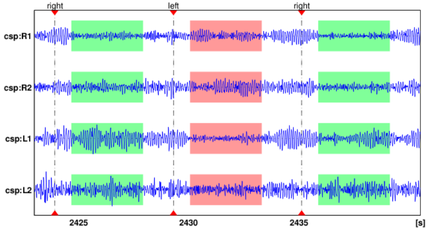

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$$\max_{\mathbf{w}} \frac{\mathbf{w}^\top \mathbf{\Sigma}_+ \mathbf{w}}{\mathbf{w}^\top \{\mathbf{\Sigma}_+ + \mathbf{\Sigma}_-\} \mathbf{w}},$$

where $\mathbf{w}$ is the spatial filter and $\mathbf{\Sigma}_+$ and $\mathbf{\Sigma}_-$ are the average covariance matrices from class 1 and 2, respectively.

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$$P(\mathbf{w}) = \sum_k \left| \mathbf{w}^\top \boldsymbol{\Sigma}_c^{(k)} \mathbf{w} - \mathbf{w}^\top \boldsymbol{\Sigma}_c \mathbf{w} \right|,$$

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Problem: If we add this quantity to the denominator, it won't be a generalized eigenvalue problem of the form $\frac{\mathbf{w}^T A \mathbf{w}}{\mathbf{w}^T B \mathbf{w}}$ anymore.

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Intuition: Treat variations to both sides in a similar way before projecting. This gives an upper bound to the quantity which we wanted to minimize.

Experimental Results

Dataset and Setup

- We tested sCSP and CSP on a data set of 80 subjects performing motor imagery with the left and right hand or with the feet.

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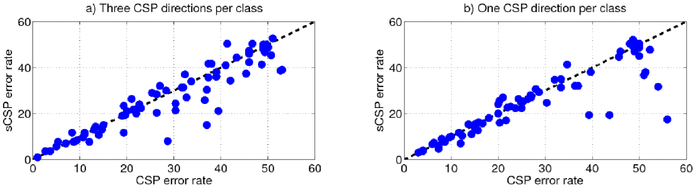
- We selected a fixed number of filters per class.
- The regularization parameter and the chunk size (1, 3 and 5) of sCSP were selected by cross-validation.

Classification Performance



Chunk size	Error rate			
	0 – 15	15 – 30	> 30	all
CV selected	0.0599	0.6642	**0.0069**	**0.0068**
1	0.0567	0.5194	**0.0085**	**0.0066**
3	0.1749	0.3547	**0.0121**	**0.0087**
5	0.1568	0.6690	**0.0076**	**0.0091**

Table: Overview of p-values for different chunk sizes and different error regions when using one-sided t-test with the hypothesis that sCSP performs better than CSP. Bold values are significant when $\alpha = 0.05$.

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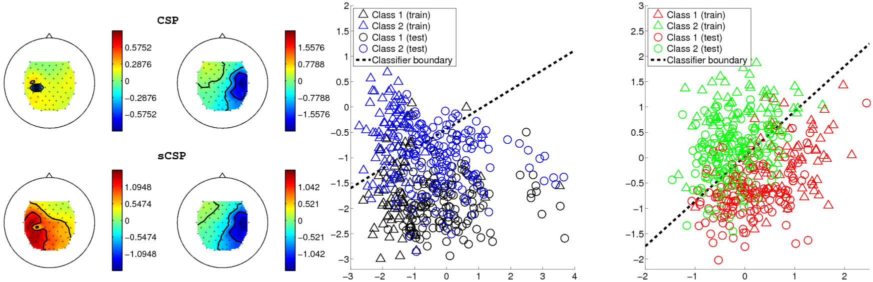

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- sCSP significantly increases classification accuracy, especially for subjects who perform badly.
- Unlike other methods our approach is completely data-driven and does not require additional recordings or models of the expected change that occurs in the EEG.
- We also showed (not presented here) that a combination of stationary features and unsupervised adaptation further improves classification performance.

Questions ?