Motor Imagery based BCI Classification via Sparse Representation of EEG Signals

Brain Computer Interface

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Outline

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- Proposed Scheme
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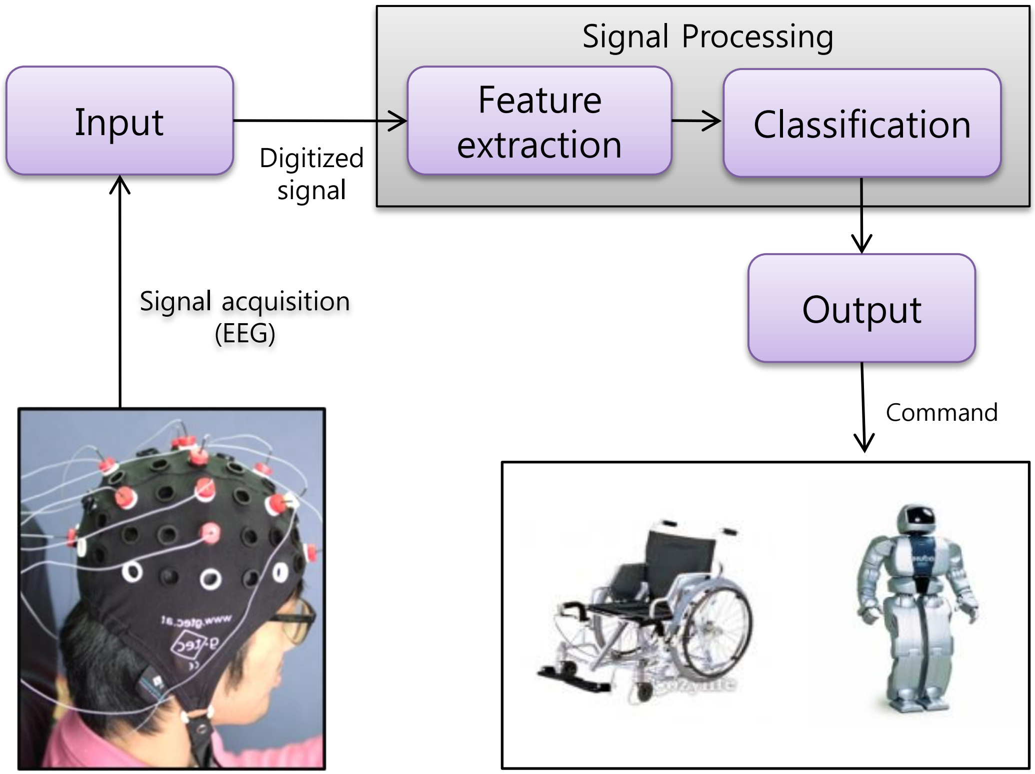
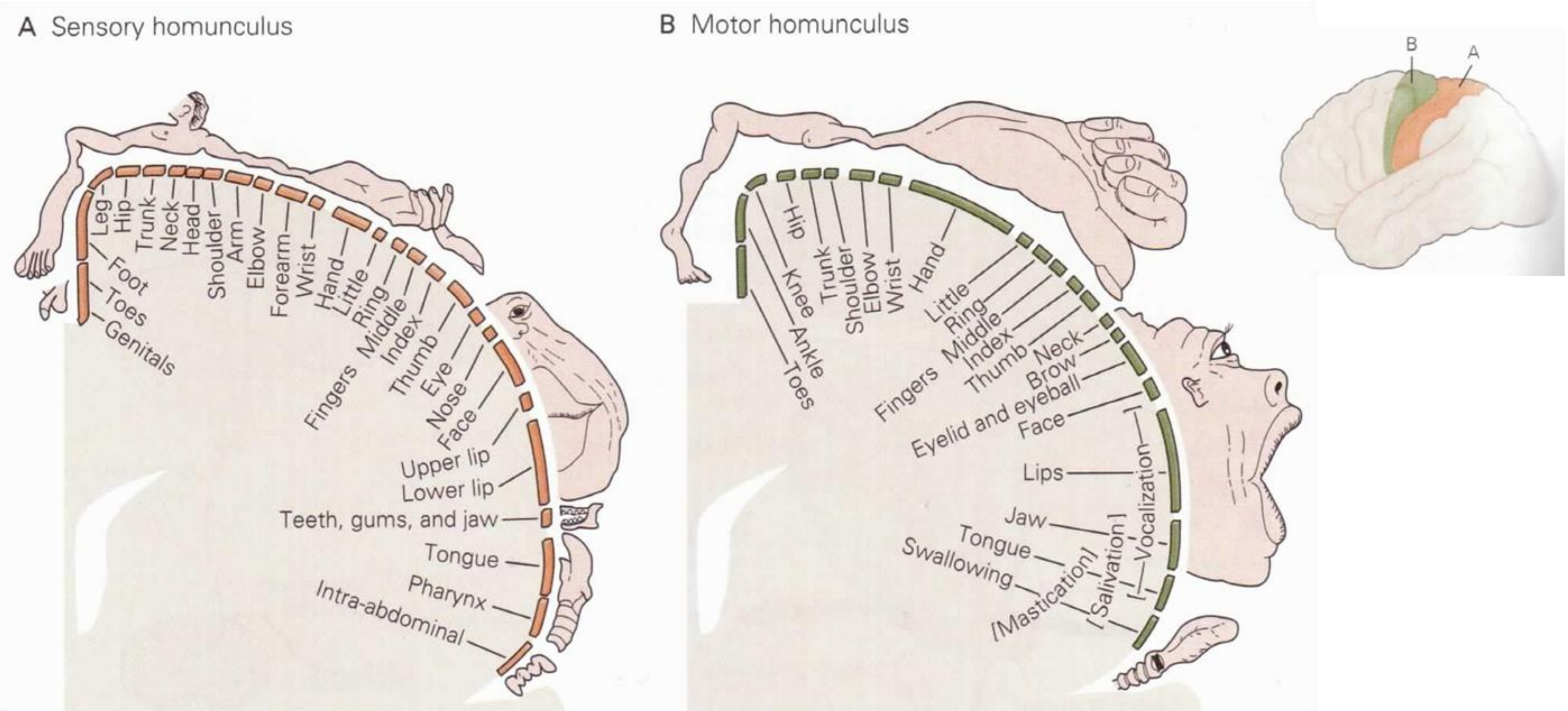
EEG based BCI

- Brain Computer Interface system



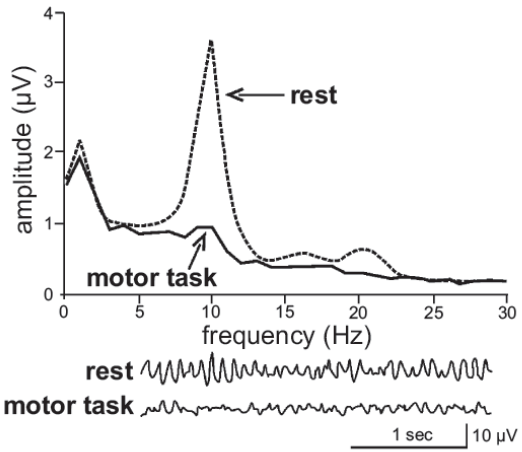
Sensory and Motor mapping



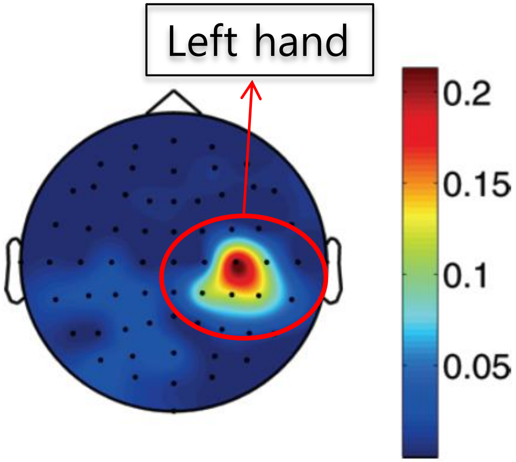
[Neuroprosthetics: Theory and Practice, K.W. Horch & G.S. Dhillon]

Motor imagery based BCI

- Mu and Beta rhythm(SMR) analysis [Wolpaw 1991]
  - The mu(8-12Hz) and/or Beta(15~30Hz) rhythms originate above the motor cortex.
  - When we imagine the left hand movement, amplitude attenuation of mu rhythm appears at the contralateral area of cortex.



< Spectral focus >



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Sparse Representation (SR)

- Sparse Representation has received a lot of attentions in recent years.
- The problem of the SR is to find for the most compact representation of a signal in terms of linear combination of atoms in an overcomplete dictionary. [Huang 2006]
- The problem of SR is to find the coefficient $\mathbf{x} \in \mathbb{R}^{N \times 1}$:

$$\hat{\mathbf{x}} = \min_{\mathbf{x}} \|\mathbf{x}\|_0 \quad \text{subject to} \quad \mathbf{y} = \mathbf{A}\mathbf{x}$$

where, $\mathbf{A} \in \mathbb{R}^{M \times N}$ is given over-complete dictionary$(M \ll N)$

$\mathbf{y} \in \mathbb{R}^{M}$ is given signal

- Where $\|\mathbf{x}\|_0$ is the ell-0 norm. Solving this minimization is NP hard
- Recently developed Compressive Sensing theory [Donoho 2006] reveals that if solution is sparse enough, ell-1 norm solution is equivalent to the ell-0 norm solution.

$$\hat{\mathbf{x}} = \min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{subject to} \quad \mathbf{y} = \mathbf{A}\mathbf{x}$$

Motivation and Purpose

- The sparse representation can be used for a number of applications including noise reduction, compression, and pattern recognition.
- Classification based on Sparse Representation was studied in Face Recognition area [Wright 2009].
- Feature extraction and classification are also key parts of BCIs.
- In this study, we apply the sparse representation to the motor imagery based BCI classification.
- Using Mu and Beta rhythms as a BCI feature, we aim to develop a new Sparse Representation based Classification (SRC) method.

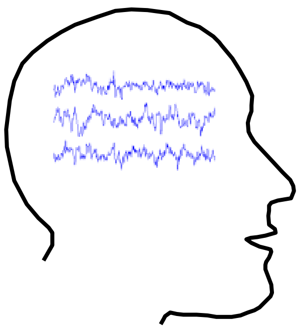
Data acquisition

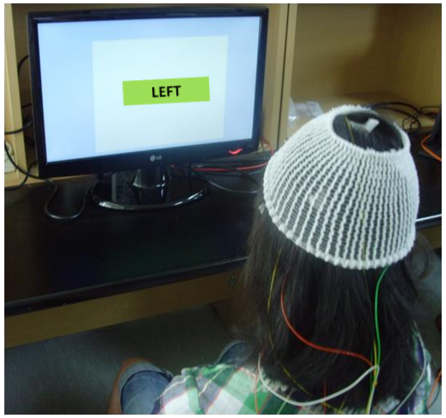
PZ3 Amplifier

RZ5 Workstation

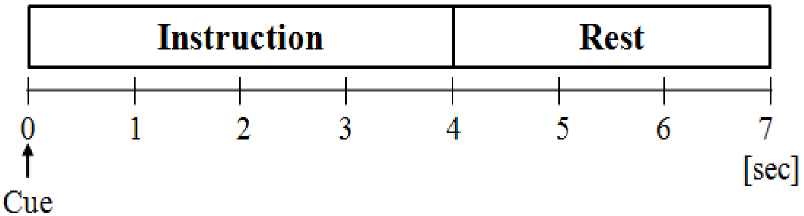
Desktop

EEG signal





Training



- We have two classes

  : Left and Right hand imaginary movement

CSP(Common Spatial Pattern)

- To reduce the dimension of feature vector and make distinguishable features, we use the CSP method.
- CSP is a powerful signal processing technique suitable for EEG-based BCIs [Blankertz 2008].
- CSP filters maximize the variance of the spatially filtered signal under one condition while minimizing it for the other condition.
  - Compute covariance matrix

$$C_R = X_R X_R^T$$

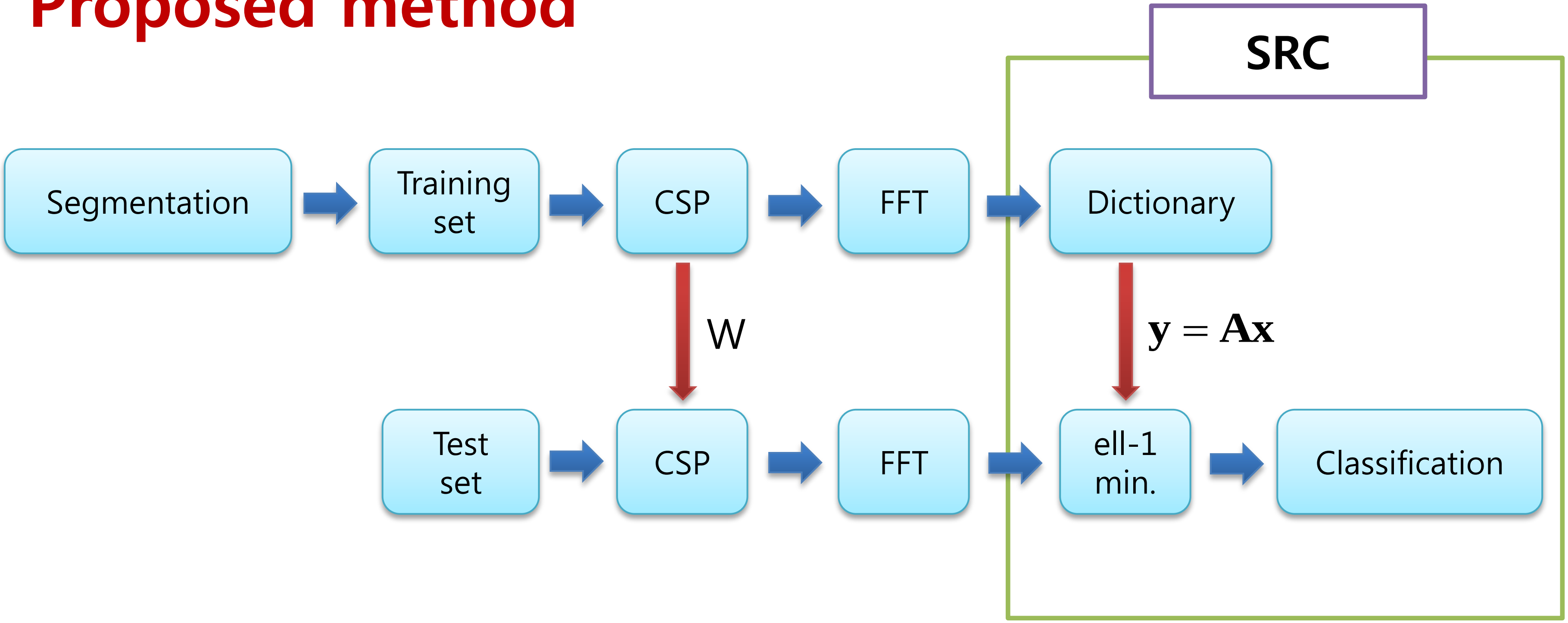
$$C_L = X_L X_L^T$$

  - Find vectors w satisfying the following optimization problems

$$\max_w \left(\frac{w_i^T C_R w_i}{w_i^T C_L w_i} \right)$$

$$\Rightarrow \min_w \left(-w_i^T C_R w_i \right) \quad \text{subject to } w_i^T C_L w_i = 1$$

Proposed method



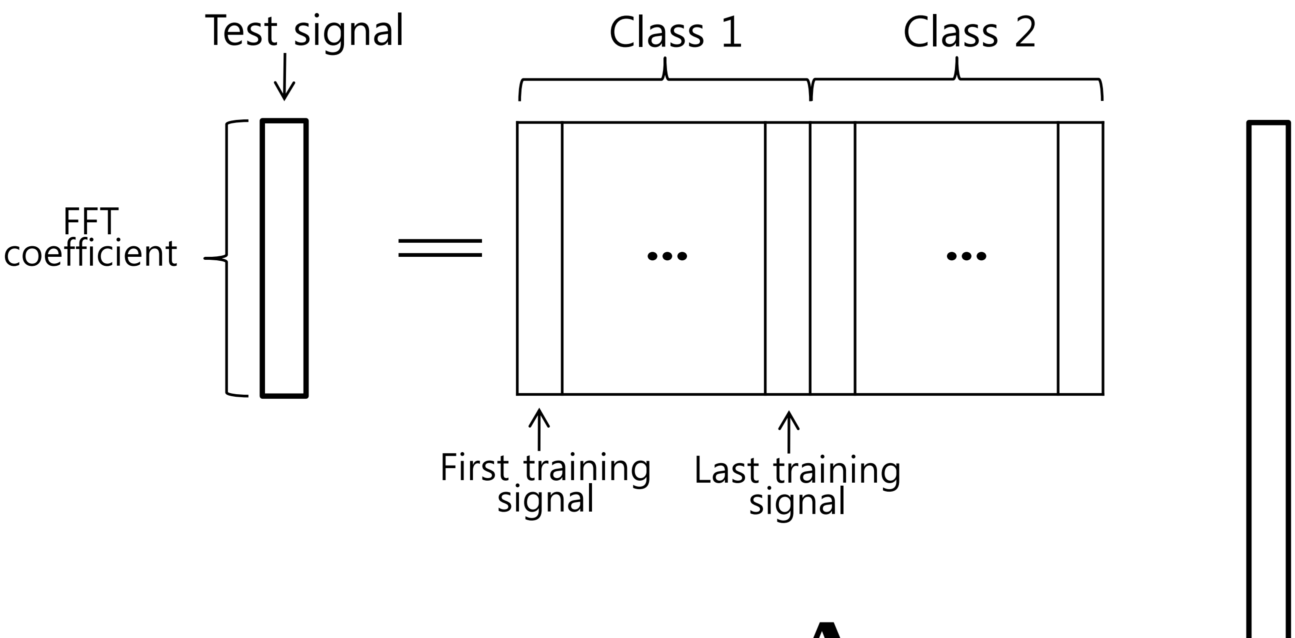
- Using training data set we can find CSP filter W .
- To use mu and beta rhythms as a BCI feature, we have taken the FFT
- We propose a new sparse representation based classification (SRC) method using dictionary and ell-1 minimization

Design a dictionary

- CSP filtering
- FFT (8~15Hz)
- vectorization

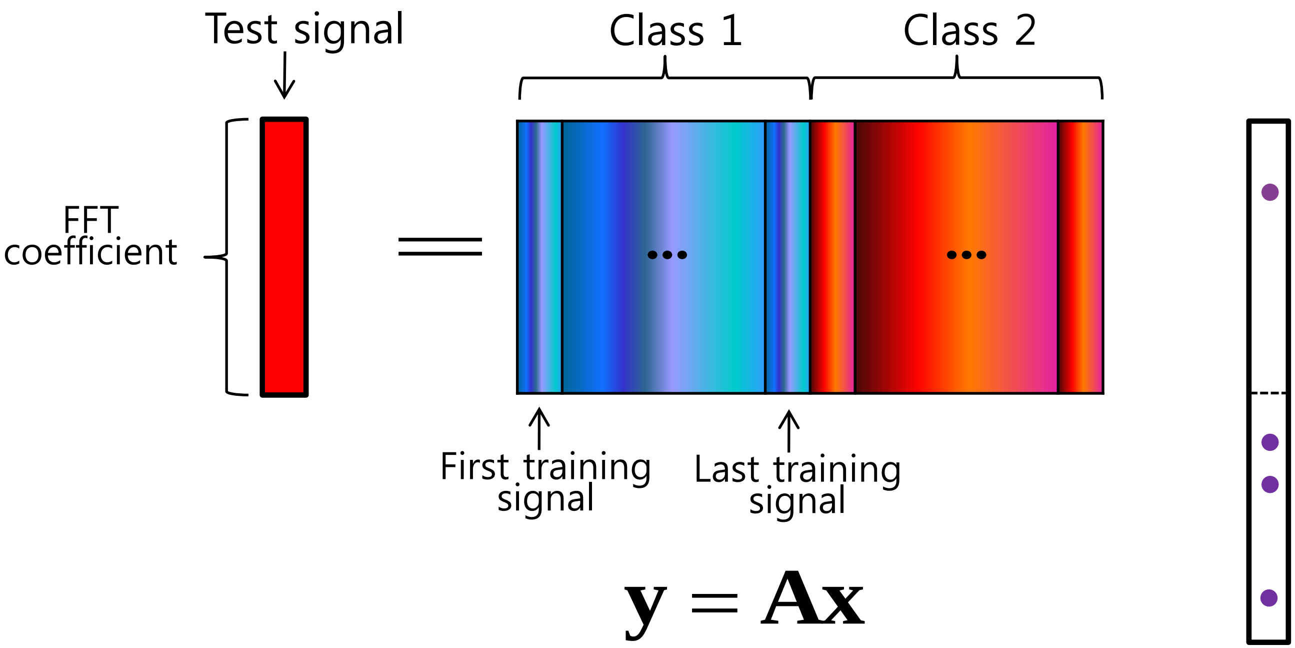
$$\mathbf{A}_i = [\mathbf{a}_{i,1}, \mathbf{a}_{i,2}, \ldots, \mathbf{a}_{i,N_t}]$$

$$\mathbf{A} := [\mathbf{A}_L ; \mathbf{A}_R]$$



$$\mathbf{y} = \mathbf{A}\mathbf{x}$$

Sparse representation



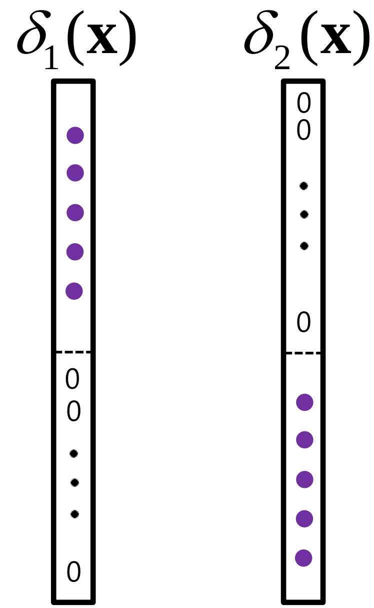
$$\mathbf{y} = \mathbf{A}\mathbf{x}$$

- This sparse representation can be solved by ell-1 minimization [Candès 2006].
- For example, a test signal **y** of class 2 can be sparsely represented as the training signals of class 2.
- However, EEG signals are very noisy, nonzero coefficients may appear in the indices corresponding to the class 1.

Classification based on Sparse Representation

- To make use of the sparse representation result in a classification problem we use characteristic function δ.

[Wright2009]



$$\hat{\mathbf{x}} = \min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{subject to} \quad \mathbf{y} = \mathbf{A}\mathbf{x}$$

$$r_i(\mathbf{y}) := \|\mathbf{y} - \mathbf{A}\delta_i(\mathbf{x})\|_2$$

- For each class *i*, $\delta_i(\mathbf{x})$ is obtained by nulling all the elements with corresponding to the other class.
- We can obtain residuals for each class.
- We determine the class *i* that has minimum residuals.

$$\text{class}(\mathbf{y}) = \arg \min_i r_i(\mathbf{y})$$

Accuracy evaluation

- We have analyzed four data sets.

Subjects	# of EEG channels	# of total trials
A	32	200
B	32	100
C	12	60
D	12	60

- All subjects are novice in the BCI experiment.
- We compare performance of the proposed SRC with the LDA(linear discriminant analysis) method.
- To make fair comparison, we also use the CSP filtering, the FFT, and the Mu(8~14Hz) and/or the Beta(15~30Hz) rhythms in the LDA classification method

Classification accuracy of subject A and B

Subject	# of trainin g signals	# of test sig nals	Accuracy (%)	
			LDA	*SRC*
A (total 200 signals)	150	50	63.50	71.25
	160	40	67.75	75.50
	180	20	68.50	77.75
	190	10	69.25	79.50
	199	1	68.75	79.00
B (total 100 signals)	50	50	67.50	71.50
	80	20	68.00	80.00
	90	10	69.50	82.50
	95	5	72.00	82.00
	99	1	72.50	82.00

- For both subject A and B, the accuracy of the SRC is better than that of the LDA method

Classification accuracy of subject C and D

Subject	# of trainin g signals	# of test sig nals	Accuracy (%)	
			LDA	*SRC*
C (total 60 signals)	40	20	89.17	91.67
	50	10	89.17	91.67
	55	5	89.17	90.84
	58	2	88.33	91.67
	59	1	88.33	91.67
D (total 60 signals)	40	20	80.83	77.50
	50	10	85.83	81.67
	55	5	86.67	78.33
	58	2	84.17	85.00
	59	1	85.00	86.67

- For subject C, SRC is better than LDA.
- For subject D, when the number of training signals increases, SRC is better than LDA.
- In this case, the number of training trials is not large enough.

Conclusions

- In this study, we propose a new sparse representation based classification (SRC) method for the motor imagery based BCI system.
- This method needs a well constructed dictionary matrix consisted of training signals.
- We use the CSP filtering and the FFT to produce the columns of the dictionary matrix.
- Our proposed SRC method shows better classification accuracy than LDA method which is well known for BCI classification.

Thank you
Any questions?

Reference

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