Motor Imagery Classification Using Multiresolution Analysis and Sparse Representation of EEG Signals

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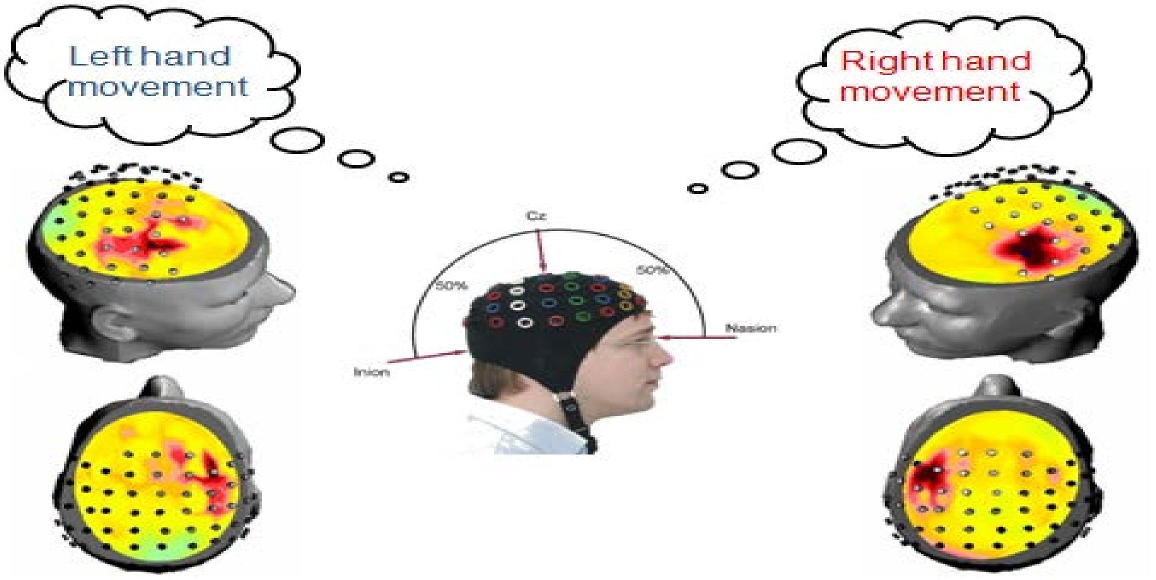
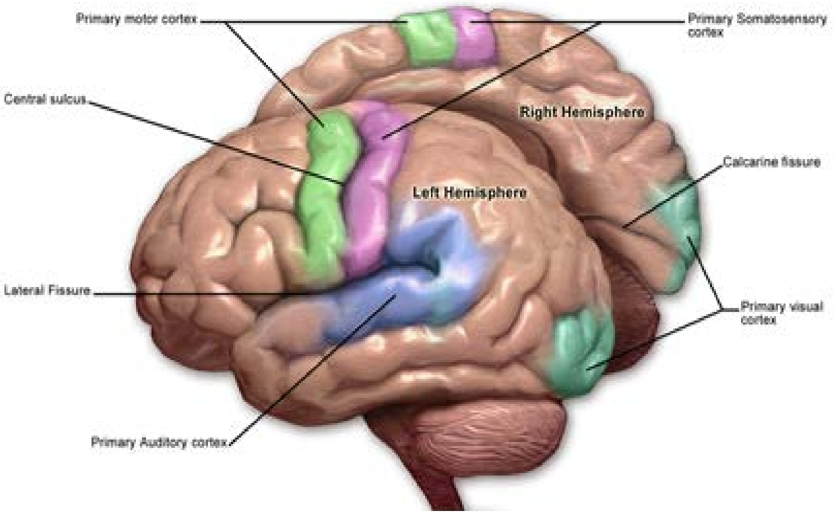
Motor Imagery Brain Signals

- Problem: Classifying motor imagery brain signals (imagined movement of limbs)



Motor Imagery Brain Signals

- Goal: Use less data and efficient algorithms to support real-time BCI.
- Approach:
  - Exploit sparse characteristics of EEGs.
  - Energies in different frequency sub-bands of the Wavelet Packet decomposition of EEG trials from few electrodes near the sensorimotor cortex.



Related works

- Using Wavelet transforms to extract features. (G. Garcia et al. 2003)
- Using Autoregressive coefficients (R. Boostani, et al. 2007)
- Most related work

Sparse representation-based classification scheme for motor imagery-based brain–computer interface systems(Y Shin, et al. 2012)

Outline

- EEG characteristics
- Feature extraction technique
- Proposed method based on sparse characteristics of EEG signals
- Results
- Conclusion

EEG Characteristics

- Two types of rolandic mu rhythm can be distinguished in the alpha band.

1. The lower-frequency mu rhythm between 8-10 Hz.
2. The higher frequency mu rhythm between 10-13 Hz.

EEG Characteristics

- Event-driven changes in the power of the EEG signals in particular frequency sub-bands are shown to improve the performance of BCI. (Pfurtschler 2003)

- In this paper we use energies, related to different frequency sub-bands motivated by the existence of different levels within the alpha band.

Pre-processing

- One of the most promising techniques in EEG signal processing is Common Spatial Patterns (CSP)[Ramoser-2000].

- CSP aims to project the data along a direction for which the trials from one class have maximum variance and the trials from the other class have minimum variance.

Wavelet Packet Decomposition

- Using time-frequency methods for non-stationary signals such as EEG can improve the performance of the classification techniques.
- Wavelet Packet Decomposition can be described using the filter-bank approach.

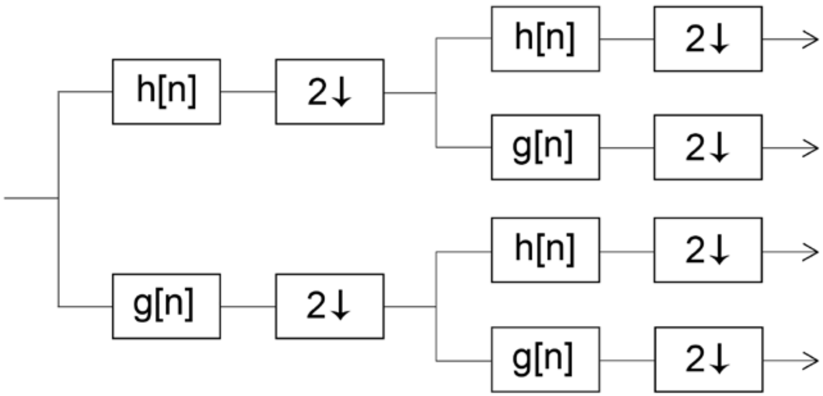


Fig-1 Wavelet Packet Decomposition

Feature Extraction

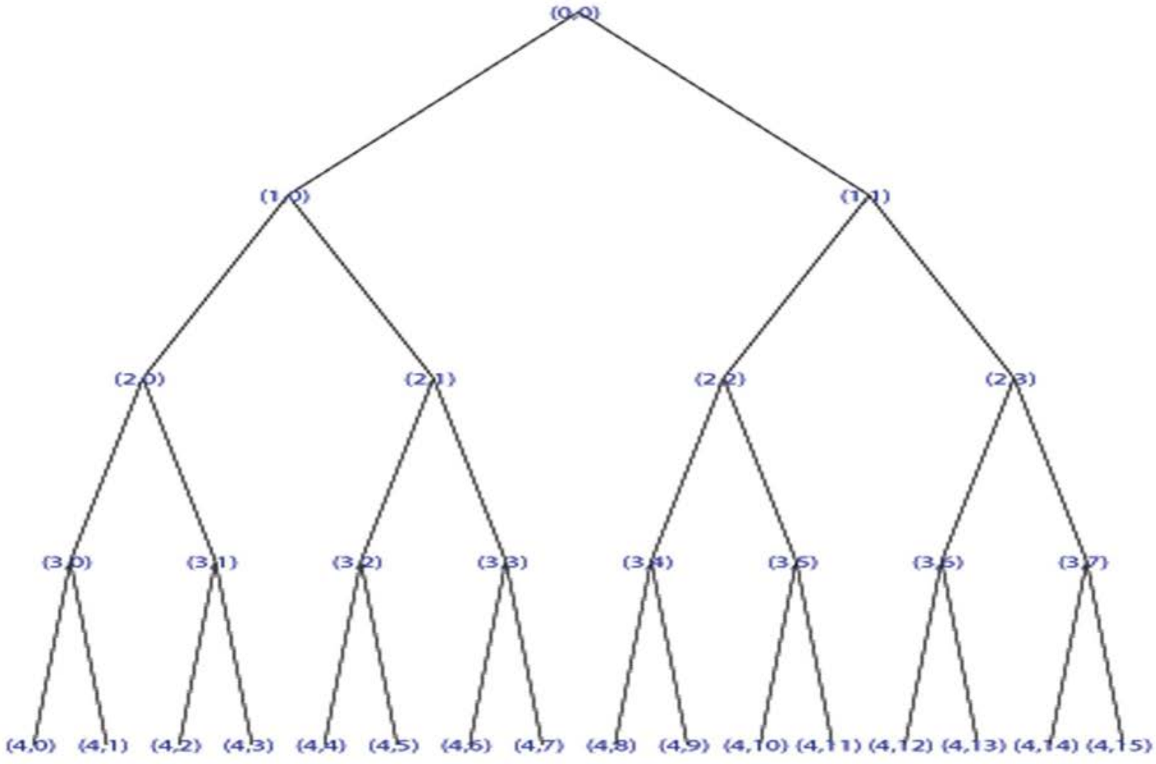


Fig 2 Energies are computed In 16 frequency sub-bands

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Feature Extraction

- The entropy of a signal z is calculated from the wavelet coefficients, using

$$Entropy(z) = -\sum_i s_i^2 \log s_i^2$$

where s_i is the i-th wavelet coefficient of z obtained from WPT.

$$\begin{bmatrix} y_1^1 & y_2^1 & \dots & y_Q^1 \\ \vdots & & & \\ y_1^N & y_2^N & \dots & y_Q^N \end{bmatrix} \xrightarrow{CSP} [z_1 \quad \dots \quad z_Q] \xrightarrow{wavelet\ coef\ energy} [x_1^{apx} \quad x_1^d \quad \dots \quad x_L^d] \xrightarrow{Entropy\ concatenated} [x_1^{apx} \quad x_1^d \quad \dots \quad x_L^d \quad ent]$$

sparse representation of EEG signals

- In this work, we approximate the measurement vectors by linear combinations of a small number of atoms from a dictionary.

$$\begin{bmatrix} y_1^1 & y_2^1 & \dots & y_Q^1 \\ \vdots & & & \\ y_1^N & y_2^N & \dots & y_Q^N \end{bmatrix} \xrightarrow{CSP} [z_1 \quad \dots \quad z_Q] \xrightarrow{wavelet\ coef\ energy} [x_1^{apx} \quad x_1^d \quad \dots \quad x_L^d]$$

$$\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_B \end{bmatrix} \cong \begin{bmatrix} a_{11}^m & a_{21}^m & \dots & a_{N_m 1}^m \\ a_{12}^m & a_{22}^m & \dots & a_{N_m 2}^m \\ \vdots & \vdots & \vdots & \vdots \\ a_{1B}^m & a_{2B}^m & \dots & a_{N_m B}^m \end{bmatrix} \begin{bmatrix} \alpha_1^m \\ \alpha_2^m \\ . \\ . \\ . \\ \alpha_{N_m}^m \end{bmatrix}$$

sparse representation of EEG signals

Therefore, the test signal is approximated using K atoms from the dictionary as

$$x = \alpha_{\lambda_1} a_{\lambda_1} + \alpha_{\lambda_2} a_{\lambda_2} + \cdots + \alpha_{\lambda_k} a_{\lambda_k}$$

where $\Lambda = \{\lambda_1, \lambda_2, \dots, \lambda_k\}, k = 1, \dots, K$ is the support of the sparse vector.

sparse representation of EEG signals

- Training samples from M classes generate M sub-dictionaries of a $B \times N$ dictionary A,

where $N = \sum_{m=1}^{M} N_m$.

$$
\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_B \end{bmatrix} \cong
\begin{bmatrix}
\overbrace{\begin{matrix} a_{11}^{1} & \cdots & a_{N_m 1}^{1} \\ a_{12}^{1} & \cdots & a_{N_m 2}^{1} \\ \vdots & \vdots & \vdots \\ a_{1B}^{1} & \cdots & a_{N_m B}^{1} \end{matrix}}^{\text{Right Hand}} &
\overbrace{\begin{matrix} a_{11}^{2} & \cdots & a_{N_m 1}^{2} \\ a_{12}^{2} & \cdots & a_{N_m 2}^{2} \\ \vdots & \vdots & \vdots \\ a_{1B}^{2} & \cdots & a_{N_m B}^{2} \end{matrix}}^{\text{Foot}}
\end{bmatrix}
\begin{bmatrix} \alpha_1^2 \\ . \\ \alpha_{N_m}^2 \\ \alpha_1^2 \\ . \\ \alpha_{N_m}^2 \end{bmatrix}
$$

sparse representation of EEG signals

- After obtaining the sparse representation of a test signal, it can be classified by computing residuals as

$$r^m(x) = \left\|x - A^i \hat{a}^m\right\|_2, m = 1,2,\dots,M$$

where $\hat{a}^m$ denotes the entries of the sparse vector associated with the m-th-class sub-dictionary.

$$class(x) = arg_{m=1,2,\dots,M} min\, r^m(x)$$

Test Data

Train Data

$$\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_B \end{bmatrix} \cong \begin{bmatrix} \overbrace{a^1_{11} & \dots & a^1_{N_m 1}}^{\text{Right Hand}} & \overbrace{a^2_{11} & \dots & a^2_{N_m 1}}^{\text{Foot}} \\ a^1_{12} & \dots & a^1_{N_m 2} & a^2_{12} & \dots & a^2_{N_m 2} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ a^1_{1B} & \dots & a^1_{N_m B} & a^2_{1B} & \dots & a^2_{N_m B} \end{bmatrix} \begin{bmatrix} \alpha^2_1 \\ . \\ \alpha^2_{N_m} \\ \alpha^2_1 \\ . \\ \alpha^2_{N_m} \end{bmatrix}$$

sparse representation of EEG signals

- To recover the sparse vector α, we need to solve the following optimization problem:

$$min\|\alpha\|_0$$

$$subject\ to\ A\alpha = x$$

- This problem is generally NP-hard. It can be written as

$$min\|A\alpha - x\|_2$$

$$subject\ to\ \|\alpha\|_0 \leq K_0$$

where K_0 is an upper bound on the sparsity level.

- To solve the optimization problem, Orthogonal Matching Pursuit (OMP) greedy algorithm is used.

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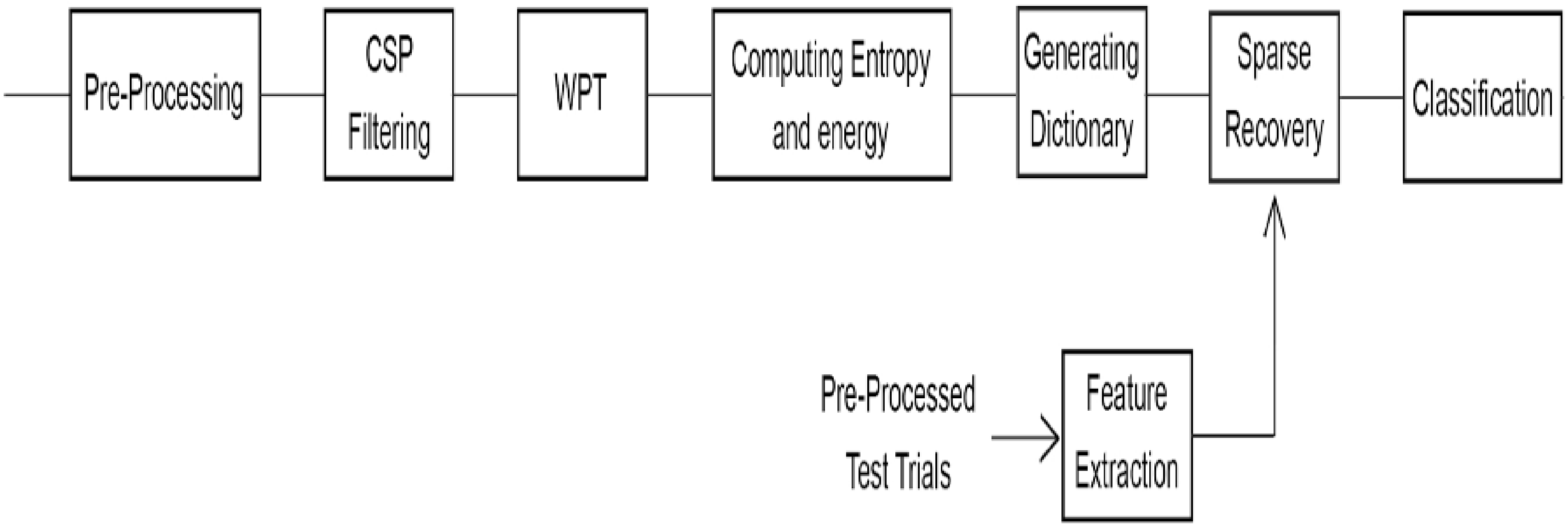
Methodology



Dataset

dataset 4a*:* provided by Fraunhofer FIRST, Intelligent Data Analysis Group and the Charite-University Medicine Berlin, Department of Neurology, Neurophysics Group.

- This data set consists of signals of five healthy subjects.

The visual indicator lasts for 3.5 seconds

a rest period begins with a random length of 1.75 to 2.25 seconds.

Dataset

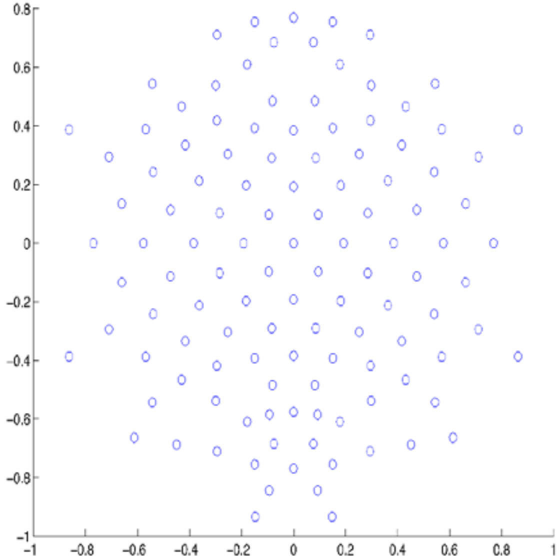


Fig 3-a Position of all the 118 electrode

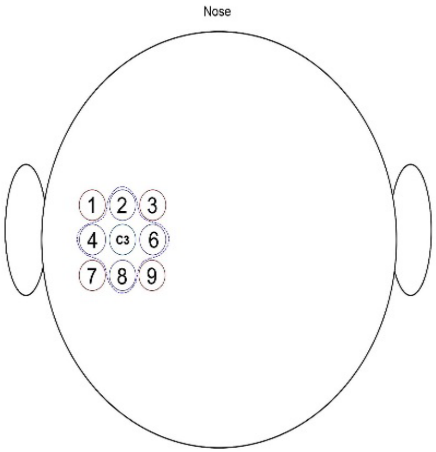


Fig 3-b Position of the five electrodes that are used.

Results

Table 1 Classification Accuracy rate (%)

Features	Subject 1	Subject 2	Subject 3	Subject 4	Subject 5
Wavelet Coefficients	64.46	73.89	54.11	75.71	64.96
Energy	64.79	85.50	61.51	73.11	59.36
Energy & Entropy	64.71	89.71	64.25	93.07	83.71
Method proposed by Y. Shin (2012)	57.29	87.25	60.14	75.07	83.43

Conclusion

- In this work, we proposed an algorithm to classify motor imagery EEG signals to support real time BCI.
- Dimensionality is reduced by selecting only five electrodes.
- We leverage the Sparse representation of the EEG trials in a multiclass dictionary learned from wavelet characteristics of the signals.
- Energy and Entropy related features enables efficient classification.

Conclusion

- This underscores the relevance of the energies and their distribution in different frequency sub-bands.

CSP

- Covariance matrices are transformed Using a whitening transformation derived from the eigenvector and eigenvalue factorization of the composite spatial covariance to S_1 and S_2.
- $S_1 = V\Sigma_1 V^T$ and $S_2 = V\Sigma_2 V^T$, then $\Sigma_1 + \Sigma_2 = 1$,
- where V Is the eigenvector matrix and Σ_1 and Σ_2 are the digonalized eigenvalue matrix.
- Hence:

The eigenvectors corresponds to the largest eigenvalue of one class, also corresponds to the smallest eigenvalue of the second group.