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

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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

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.
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.
One of the most promising techniques in EEG signal processing is Common Spatial Patterns (CSP)\cite{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.
Feature Extraction

Fig 2 Energies are computed in 16 frequency sub-bands
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.
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^1_2 & \ldots & y^1_Q \\
y^2_1 & y^2_2 & \ldots & y^2_Q \\
\vdots & \vdots & & \vdots \\
y^N_1 & y^N_2 & \ldots & y^N_Q \\
\end{bmatrix} \approx \begin{bmatrix}
w^{11}_1 & w^{12}_1 & \ldots & w^{1B}_1 \\
w^{21}_1 & w^{22}_1 & \ldots & w^{2B}_1 \\
\vdots & \vdots & & \vdots \\
w^{N1}_1 & w^{N2}_1 & \ldots & w^{NB}_1 \\
\end{bmatrix} \alpha^1_1 \alpha^2_1 \ldots \alpha^N_1 \alpha^1_2 \alpha^2_2 \ldots \alpha^N_2 \ldots \alpha^1_B \alpha^2_B \ldots \alpha^N_B \alpha^1_{m1} \alpha^2_{m1} \ldots \alpha^N_{m1} \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots 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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 $\Lambda = \{\lambda_1, \lambda_2, \ldots, \lambda_k\}$, $k = 1, \ldots, K$ is the support of the sparse vector.
Training samples from $M$ classes generate $M$ sub-dictionaries of a $B \times N$ dictionary $A$,

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

\[
\begin{bmatrix}
  x_1 \\
  x_2 \\
  \vdots \\
  x_B
\end{bmatrix} \in \mathbb{R}^{B \times N} =
\begin{bmatrix}
  a_{11}^1 & \ldots & a_{N_m1}^1 & a_{11}^2 & \ldots & a_{N_m1}^2 \\
  a_{12}^1 & \ldots & a_{N_m2}^1 & a_{12}^2 & \ldots & a_{N_m2}^2 \\
  \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\
  a_{1B}^1 & \ldots & a_{N_mB}^1 & a_{1B}^2 & \ldots & a_{N_mB}^2
\end{bmatrix} \alpha =
\begin{bmatrix}
  \alpha_1^1 \\
  \alpha_1^2 \\
  \vdots \\
  \alpha_{N_m}^1 \\
  \alpha_{N_m}^2
\end{bmatrix}
\]
After obtaining the sparse representation of a test signal, it can be classified by computing residuals as

\[ r^m(x) = \| x - A^i \hat{a}^m \|_2, m = 1, 2, \ldots, M \]

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

\[ \text{class}(x) = \arg_{m=1,2,\ldots,M} \min r^m(x) \]
To recover the sparse vector $\alpha$, 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.
Methodology

Pre-Processing → CSP Filtering → WPT → Computing Entropy and energy → Generating Dictionary → Sparse Recovery → Classification

Pre-Processed Test Trials → Feature Extraction → Global SIP 2015
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.
Fig 3-a Position of all the 118 electrode

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

Dataset

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## Results

Table 1 Classification Accuracy rate (%)

<table>
<thead>
<tr>
<th>Features</th>
<th>Subject 1</th>
<th>Subject 2</th>
<th>Subject 3</th>
<th>Subject 4</th>
<th>Subject 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wavelet Coefficients</td>
<td>64.46</td>
<td>73.89</td>
<td>54.11</td>
<td>75.71</td>
<td>64.96</td>
</tr>
<tr>
<td>Energy</td>
<td>64.79</td>
<td>85.50</td>
<td>61.51</td>
<td>73.11</td>
<td>59.36</td>
</tr>
<tr>
<td>Energy &amp; Entropy</td>
<td>64.71</td>
<td>89.71</td>
<td>64.25</td>
<td>93.07</td>
<td>83.71</td>
</tr>
<tr>
<td>Method proposed by Y. Shin (2012)</td>
<td>57.29</td>
<td>87.25</td>
<td>60.14</td>
<td>75.07</td>
<td>83.43</td>
</tr>
</tbody>
</table>
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 $\Sigma_1$ and $\Sigma_2$ are the diagonalized eigenvalue matrix.

- Hence:

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

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