Classification of Electro-encephalographic Spatial Patterns

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Abstract The aim of this study is to describe a general approach to determine important electrode positions in the case when the measured EEG-signal is used for classification. To classify planning of movement of right and left index finger, three different approaches were compared: classification using a physiologically motivated set of four electrodes, a set determined by principal component analysis and electrodes determined by spatial pattern analysis. Spatial pattern analysis enhanced the classification rate significantly from 61.3 $\pm 1.8\%$ (with four electrodes) to 71.8 $\pm 1.4\%$ whereas the classification rate using the principal component analysis is significantly lower (65.2 $\pm 1.4\%$). Most of the 61 electrodes used had no influence on the classification rate so that in future experiments the setup can be simplified drastically to 6 to 8 electrodes without loss of information.

1 Introduction

In many clinical studies using EEG as a measuring device, it is important to determine which electrodes carry significant information and which do not. Especially when using modern EEG-equipment with 32, 64 or even more electrodes it is often preferable to concentrate on a subset of electrodes. The process of selecting relevant electrode positions is a major problem when classifying single-trail EEG signals in real time to forecast the side of finger movements. With help of the measured time series various physiologically motivated quantities can be calculated which build up a feature vector. Adding the feature vectors of several electrodes, the problem of differentiating brain states is then reduced to the mathematical problem of classifying vectors in a high dimensional space. This paper was aimed at comparing the following approaches: 1) classification with four out of 61 electrodes motivated by physiological considerations, 2) classification with electrodes determined by principal component analysis (PCA) and 3) by spatial pattern analysis introduced by [6]. The general mathematical background and the results of data processing of five subjects are presented and discussed.

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2 Experimental set-up and data recording

The EEG was measured from 61 equidistant scalp positions on both hemispheres following the 10-20-system [4] with additional electrodes at the interspaces using a 64-channel EEG system (NeuroScan). Since the outer electrodes were distorted by muscle artifacts, only the 42 inner electrodes were used for analysis as displayed in Fig.1. The signal was band pass filtered (0.1 to 40 Hz) and the sampling rate was 125 Hz. For a more detailed discussion see [8]. This procedure lead to approx. 300 artifact free trials for each subject, with approx. 150 trials for left and right index finger movements.

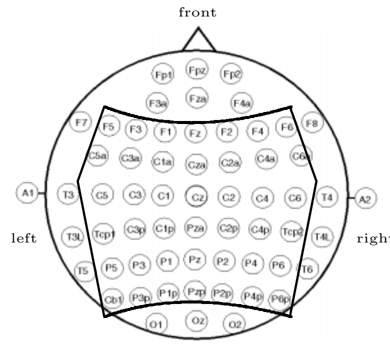


Figure 1: The 61 electrode setup. The 42 inner electrodes which are used for classification are framed.

3 Parameter estimation and feature vector

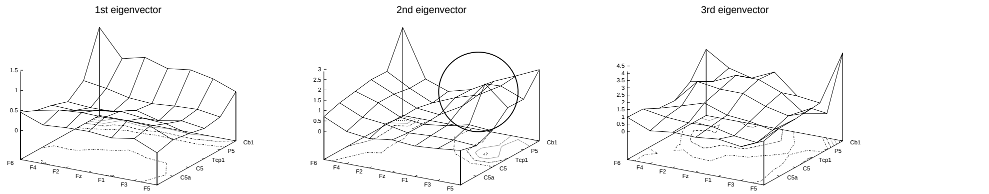
When differentiating brain states by means of the measured EEG-signal, it is important to characterize the underlying physiological processes by the recorded time series. Denoting the measured EEG-signal at any electrode at time t by $x(t)$, we used the μ-rhythm as the basis of the calculation for the feature vector $\mathbf{f}$. Characterization of the μ-rhythm was performed by calculating the spectral power in the frequency range $8 - 13\ Hz$ as proposed by [11]. Other physiological processes are the readiness potential or the ERD/ERS, see [5,9]. These features did not enhance classification rates and were therefore discarded, see [8]. The μ-rhythm feature was calculated at each of the 42 electrode sites in every trial and classification was done using the widely used multivariate approach, see [1]. Classification rates were estimated with cross-validation (95 % learning vectors, 5 % testing vectors, ten randomly chosen learning/testing sets).

4 Determining the optimal number of electrodes

4.1 The four electrode approach

A first approach is to use physiological information. Since the generator of the μ-rhythm is located in the somatosensory cortex [2,10], only those electrodes which are located over the sensorimotor cortex are considered for analysis. Based on MRI-scans with electrode locations from four of the five subjects of the study, electrodes of C3, C4, CP3 and CP4 were chosen for analysis.

a) left movements:



b) right movements:

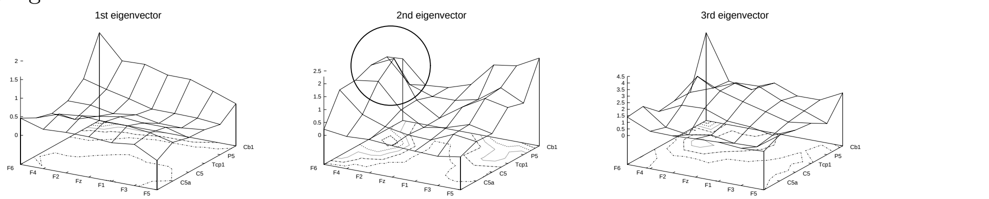


Figure 3: The first three principal components of the measured EEG signals. The asymmetric behaviour of left- and right-handed movement leads to differences in the second principal component.

4.2 The principal component analysis approach

The second approach is to calculate the principal components of the EEG signals of the left and the right movements and to use only those electrodes which form the eigenvectors with the largest singular values. Given n measurements of the feature vector $\boldsymbol{x}(t_i) \in \mathbb{R}^q$ (i=1,. . . ,n, n=number of time points, q=number of electrodes) of left or right movements, the principal component analysis (PCA) determines a signal representation with vectors $\boldsymbol{\phi}_l$ (l=1,. . . ,n) so that

$$\mathbf{x}(t_i) = \sum_{l=1}^{q} \xi_{il}\boldsymbol{\phi}_l, \quad \boldsymbol{\phi}_l \in \mathbb{R}^q.$$

When using only some of the eigenvectors for signal representation to reduce the number of electrodes (e.g. the set $\mathbf{C} \subsetneq (1, \ldots, q)$), the least-squares error is

$$\varepsilon^2 = \sum_{i=1}^{n} \left(\mathbf{x}(t_i) - \sum_{l\in\mathbf{C}} \xi_{il}\boldsymbol{\phi}_l\right)^T \cdot \left(\mathbf{x}(t_i) - \sum_{l\in\mathbf{C}} \xi_{il}\boldsymbol{\phi}_l\right) \quad = \sum_{l\notin\mathbf{C}} \lambda_l.$$

Therefore, taking the eigenvector with the largest eigenvalue is optimal in the sense of signal representation of each class. It is crucial that it is not optimal in the sense of classification although it seems highly probable that the differentiating signal, due to planning of left or right index finger movement, determines the EEG signal.

(a) spatial pattern of left movements (b) spatial pattern of right movements

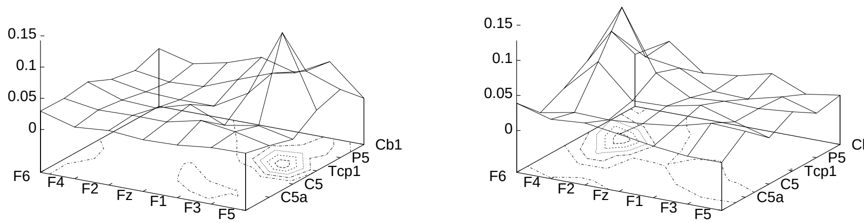


Figure 4: Spatial pattern determined with simultaneous diagonalisation. The electrodes with high impact are in accordance with the physiological information.

4.3 The spatial pattern approach

The third approach to determine the optimal electrodes aims directly at searching the set of vectors which maximizes the classification rate. The signal representation of the feature vectors of both left and right movements has to be done in the same base and we have to look for a base of eigenvectors of both covariance matrices $\mathbf{S}^1$ and $\mathbf{S}^2$ of the feature vectors of both classes. This is the mathematical problem of simultaneous diagonalisation, see [3]. If $\mathbf{S}^j$ $(j = 1, 2)$ are the covariance matrices of both classes and $\mathbf{S}^0 = \mathbf{S}^1 + \mathbf{S}^2$, then there exists an orthogonal matrix $\mathbf{P}$ with $\mathbf{P}\mathbf{S}^0\mathbf{P}^T = \mathbb{1}$ and the following equations for the transformed covariance matrices $\mathbf{T}^j = \mathbf{P}\mathbf{S}^j\mathbf{P}^T$ hold:

$$
\begin{aligned}
\mathbf{T}^1 + \mathbf{T}^2 = \mathbf{P}\mathbf{S}^1\mathbf{P}^T + \mathbf{P}\mathbf{S}^2\mathbf{P}^T &= \mathbb{1} \\
\Leftrightarrow \quad \mathbf{T}^1 = \mathbb{1} - \mathbf{T}^2. &
\end{aligned} \tag{1}
$$

If $\boldsymbol{\phi}_l^j$ and λ_l^j are the eigenvectors and eigenvalues of the transformed and whitened covariance matrices $\mathbf{T}^j$, we get with eq. 1:

$$
\begin{aligned}
\mathbf{T}^2\boldsymbol{\phi}_l^2 = \left(\mathbf{1} - \mathbf{T}^1\right)\boldsymbol{\phi}_l^2 &= \lambda_l^2\boldsymbol{\phi}_l^2 \\
\Leftrightarrow \quad \mathbf{T}^1\boldsymbol{\phi}_l^2 = (1 - \lambda_l^2)\ \boldsymbol{\phi}_l^2, & \\
\text{thus} \qquad \boldsymbol{\phi}_l^1 = \boldsymbol{\phi}_l^2 =: \boldsymbol{\phi}_l, \quad \lambda_l^1 = (1 - \lambda_l^2). &
\end{aligned} \tag{2}
$$

Equation (2) means that the eigenvector with the largest eigenvalue of the transformed covariance matrix of class one equals the eigenvector with the smallest eigenvalue of the transformed covariance matrix of class two and vice versa. This ensures a minimum least-squares error when the signals of both classes are represented by a subset of eigenvectors with large and small eigenvalues. After calculating the common eigenvectors of the transformed matrices by simultaneous diagonalisation and after whitening the matrices, the new coefficients of the feature vector can be computed.

(a) Four electrodes (b) PCA (c) Spatial pattern

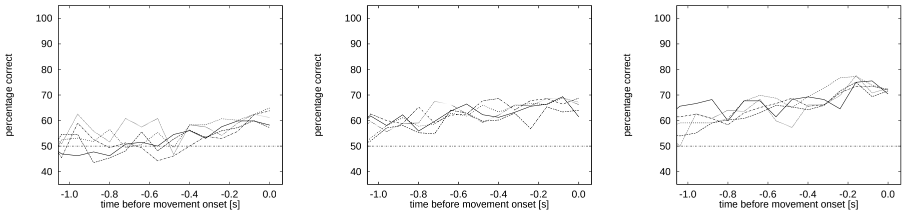


Figure 5: Time courses of the classification rates of all five subjects with the three different approaches. Movement onset is at $0.0s$.

5 Results

Fig.3 shows the first three principal components and the respective weight of each electrode of left and right movements of subject 5 determined with PCA. It is obvious that the principal components with the largest and the third largest singular value of both classes (left and right index finger movements) resemble each other. The principal components with the second largest singular value indicate the expected asymmetry due to the underlying physiological processes of left and right index finger movement. Fig.4 shows the spatial pattern of subject 5 determined with simultaneous diagonalisation. It follows from Fig. 4 that, like in the physiological approach, electrodes C3P and C4P are selected. In contrast to this approach electrode C3 has no weight at all and weight of electrode C4 is the same as of electrode P4, an electrode not considered by the first approach. To rate the three different approaches, the temporal evolution of the classification rates in the interval $[-250ms, 0ms]$ before movement onset are compared. Fig.5 shows the temporal evolution of the classification rates of every subject for the three different approaches. As expected, the classification rate at 1 s before the actual movement is 50% and no classification information can be drawn from the data. To compare the classification ability of the three different approaches we calculated the mean classification rate in the interval $[-250ms, 0ms]$. This yields a final classification rate of 61.3 $\pm$ 1.8% for the four electrode approach, 65.2 $\pm$ 1.4% for PCA and 71.8 $\pm$ 1.4% for spatial pattern analysis.

6 Discussion

Although planning of movement of left and right index finger leads to a distinguishable signal, the measured EEG time series are still dominated by physiological processes which are found at both left and right movements. Classification with help of the principal components is therefore inevitably leading to a low classification rate. This confirms the results of [7] who studied PCA as a feature extraction tool in a two electrode setting. In contrast to the PCA the spatial pattern method is able to determine the signal which is caused by the differences in the planning of movement of left and right index finger. In addition it improves the classification rate significantly and facilitates the experimental setup considerably. For every subject an optimal electrode setup can be determined.

7 Acknowledgement

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