7. Workshop Automatisierungstechnische Verfahren für die Medizin vom 19. - 21. Oktober 2007 in München

„Unsupervised Classification for Non-invasive Brain-Computer-Interfaces“

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Copyright:	VDI Verlag GmbH
Band:	Fortschritt-Bericht VDI Reihe 17 Nr. 267 „Automatisierungstechnische Verfahren für die Medizin, 7. Workshop, Tagungsband“
Editors:	Ralf Tita, Robert Riener, Martin Buss, Tim C. Lüth
ISBN:	978-3-18-326717-0
Pages:	65-66

Unsupervised Classification for Non-invasive Brain-Computer-Interfaces

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INTRODUCTION

Non-invasive Brain-Computer-Interfaces (BCIs) are devices that infer the intention of human subjects from signals generated by the central nervous system and recorded outside the skull, e.g., by electroencephalography (EEG). They can be used to enable basic communication for patients who are not able to communicate by normal means, e.g., due to neuro-degenerative diseases such as amyotrophic lateral sclerosis (ALS) (see [Vaughan2003] for a review).

One challenge in research on BCIs is minimizing the training time prior to usage of the BCI. Since EEG patterns vary across subjects, it is usually necessary to record a number of trials in which the intention of the user is known to train a classifier. This classifier is subsequently used to infer the intention of the BCI-user.

In this paper, we present the application of an unsupervised classification method to a binary non-invasive BCI based on motor imagery. The result is a BCI that does not require any training, since the mapping from EEG pattern changes to the intention of the user is learned online by the BCI without any feedback. We present experimental results from six healthy subjects, three of which display classification errors below 15%. We conclude that unsupervised BCIs are a viable option, but not yet as reliable as supervised BCIs.

The rest of this paper is organized as follows. In the Methods section, we first introduce the experimental paradigm. This is followed by a description of the methods used for spatial filtering, feature extraction, and unsupervised classification. We then present the experimental results, and conclude the paper with a brief discussion.

METHODS

Experimental Paradigm

Motor imagery of specific limbs is a frequently used paradigm for BCIs. It is well known that haptic motor imagery causes a frequency specific decrease in the variance of the electric field of the brain in that part of the motor cortex representing the specific limb [Pfurtscheller1999]. In this study, we use motor imagery of the left/right hand to intentionally induce changes in measured EEG patterns.

Spatial Filtering

One of the main problems in non-invasive BCIs is the low signal-to-noise-ratio (SNR) of the recorded data. For the experimental paradigm used here, it is known that the EEG signals that carry information about the intention of the user originate in the hand areas of the left and right motor cortex. If these signals are measured by electrodes placed over the motor cortex, they are heavily cloaked by EEG background activity from other brain areas. For this reason, we use the method of Adaptive Spatial Filters (ASF) to improve the SNR [Grosse-Wentrup2007]. The result is a two dimensional signal vector for each trial, containing estimates of the electric field of the brain originating in the left and right motor cortex.

Feature Extraction

Given estimates of the electric field of the brain originating in the left and right motor cortex, we compute the feature vector of each trial in the following way. We first extract 20 frequency bands ranging from 0 - 40 Hz, each 2 Hz wide, from each of the two signals using a sixth-order Butterworth filter. Then, we compute the variance in each of the frequency bands during motor imagery. These variances form the 40-dimensional feature vector.

Unsupervised Classification

We assume that we have a set of feature vectors, but do not know the corresponding class labels (motor imagery of left or right hand). The goal is then to determine the class label of each trial.

For each frequency band, we first fit a Gaussian mixture model with two classes to the variances of the EEG signal originating in the left and right motor cortex. This is achieved by maximizing the log-likelihood of the data using the expectation-maximization (EM) algorithm. This results in 20 Gaussian mixture models, one for each frequency band. Fig. 2 shows the resulting (normalized) clusters for one frequency band of two different subjects. For a feature vector obtained from a new trial, these clusters can be used to

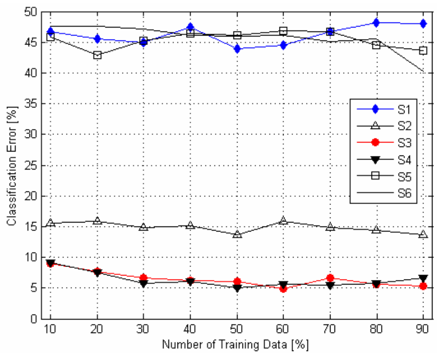

Figure 1: Classification results

assess the likelihood of the feature vector conditioned on each cluster. In principle, the new trial can then be assigned to that class label corresponding to the cluster with the highest likelihood.

This classification procedure is, however, not practical, since most frequency bands, i.e., most of the 20 Gaussian mixture models, do not provide any information on the intention of the BCI-user. It is thus necessary to identify the most discriminative frequency band. This is done by computing the likelihood of the available features of each frequency band conditioned on the wrong cluster. This serves as a measure for the separation of the two clusters. That frequency band with the lowest likelihood is then identified as the frequency band providing the most discriminative information. Subsequently, only the Gaussian mixture model of this frequency band is used for assigning a class label to a feature vector from a new trial.

Assigning feature vectors to one of the two clusters does not solve the problem of determining which cluster corresponds to which class label. This can be determined from the a-priori knowledge that motor imagery of the left hand leads to a low variance in the right and high variance in the left motor cortex and vice versa.

RESULTS

Experimental data from six healthy subjects was recorded with a 128-channel EEG, sampled at 500 Hz, with common average reference. A total of 300 trials (150 per condition) were recorded for each subject in randomized order. Each trial started with central display of a fixation cross for three seconds, which was then overlaid by an arrow pointing to the left or the right for seven seconds. The subjects were instructed to perform haptic motor imagery of the corresponding hand when seeing the arrow.

The classification results for all subjects are shown in Fig. 1, depending on the percentage of trials used for fitting the Gaussian mixture models. Subjects S3 and S4 achieve classification errors below 10%, and subject S2 shows a classification error of approximately 15%. The other three subjects did not achieve classification errors below chance. It should be pointed out that for subjects S2-S4 only 10% percent of the available trials suffice to obtain good classification results.

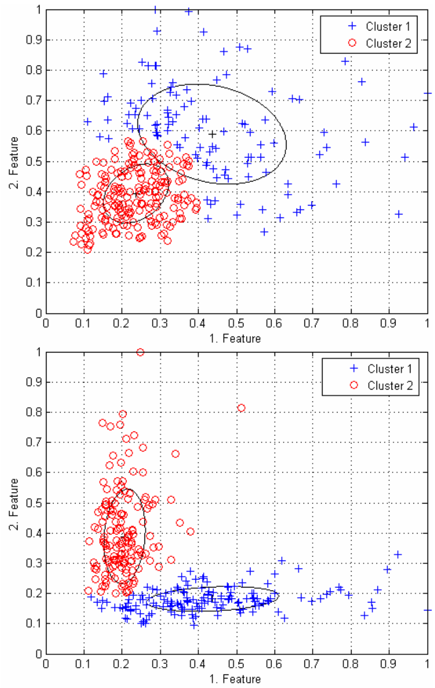

Figure 2: Clusters of the most reactive frequency band for subjects S1 (top) and S3 (bottom).

DISCUSSION

We have shown that unsupervised classification is a viable option for BCIs. The classification errors of three subjects were comparable to those obtained by supervised classification methods [Grosse-Wentrup2007], while the other three subjects did not perform above chance. The reason for this is illustrated in Fig. 2, showing the Gaussian mixture models for the most reactive frequency band of subjects S1 and S3. The features of subject S3 are clearly separated into two clusters, while this not the case for subject S1. Furthermore, the clusters for subject S1 are not meaningful, i.e., they separate the data into two classes that correspond to small/large total variance. Further research is thus needed to increase the reliability of unsupervised classification for non-invasive BCIs.

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