

Basis Selection for Increased Interclass Separability of EEG Signals

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Abstract. We present an adaptive feature selection method for the classification of EEG signals. The algorithm determines the most discriminative channels and regions of the time-frequency plane. Promising results are obtained when classifying signals associated with real and imaginary hand motion of a healthy subject.

Keywords: BCI, EEG, cosine packet transform, best basis, Kullback-Leibler divergence, classification

1. Introduction

In recent years Brain-Computer Interfaces (BCI) have proven their ability to translate human intentions and cognitive states – reflected by specific brain signals – into control signals for computer applications and neuroprosthetic devices. A review of the different steps that form a standard BCI can be found in [Nicolas-Alonso and Gomez-Gil, 2012]. In the feature selection step, the Modified Discrete Cosine Transform (MDCT, [Princen et al., 1987]) is an efficient and energy-compacting example of the many ways by which a signal can be linearly expanded. The corresponding basis may be visualized as a tiling of the time-frequency plane, delineating the regions in which most energy of the basis functions is concentrated. We propose to select a basis which maximizes the separability of two or more classes of EEG signals. The divergence between different basis coefficients may then be used to determine which spatial and time-frequency features are the most discriminative for the purpose of classification.

2. Material and Methods

Our data consists of 64-channel EEG recordings of a right handed, 26 years old male with no disabilities. The sampling rate is 512 Hz. Each trial started with the user fixating a cross on a screen for 1.5 s during which he was allowed to blink. The subject was then presented with a visual cue for 2 s. The cue was chosen randomly among a resting symbol, an arrow pointing right, and an arrow pointing left. If a directional arrow appeared, the user had to move or, depending on the session, imagine moving the corresponding ipsilateral hand. The subject had to remain motionless during the following 2 s (in case of real movement) or 4 s (in case of imagined movement). During the real movement session, the total number of trials was as follows: 88 for real left hand movement, 88 for real right hand movement, 44 for resting. During the imaginary movement session, the total number of trials was as follows: 250 for imaginary left hand movement, 250 for imaginary right hand movement, 125 for resting. Similarly acquired data of the same subject has been presented in [Fruitet et al., 2011].

As we are interested in the mu- and beta-rhythms that characterize motor activity, we start by bandpassing the EEG recordings in the 8–24 Hz range and focus on the 21 electrodes ranging from FC5 to FC6, from C5 to C6, and from CP5 to CP6. We then apply a Cosine Packet Transform (CPT) to the signals of each channel. The CPT performs a dyadic division of the time axis, computing a MDCT of each time block. The best basis algorithm by [Coifman and Wickerhauser, 1992] is employed on the resulting tree structured family of bases (each corresponding to specific tilings of the time-frequency plane) to find the normal basis which maximizes the symmetric Kullback-Leibler divergence (KL Div., [Kullback and Leibler, 1951]) between two or more classes of signals. We choose to average the computed divergence measures along all channels, so that the selected basis is the same for all channels. The basis coefficients of each signal are then ordered according to their discriminative power (again based upon the KL Div. measure). For classification purposes, a candidate EEG signal is classified as belonging to the class of signals to which the KL Div. between basis coefficients is, on average, the lowest. Our classification results are compared to the ones obtained by training a linear kernel support vector machine (SVM) with the power spectral densities (PSD) of the signals.

3. Results

Table 1 provides an overview of the classification accuracy for different binary problems as determined by leave-one-out cross-validation. For the classification tasks involving real motion only 25 % of all coefficients were used (sorted according to their discriminative power), for the imaginary tasks 50 % of all coefficients were used. The performance of the two classification methods appears to be comparable. Fig. 1(a) shows how our algorithm may be used to discern the most discriminative channel and time-frequency locations between two classes of signals. Fig. 1(b) shows how, thanks to the sparsity of MDCTs, the classification result rapidly stabilizes when considering more and more coefficients. In this case the recall rates for real left hand motion, real right hand motion, and rest are 75 %, 72 %, and 82 %, respectively.

Table 1: Recall rates of the two described classification methods applied to four different binary problems.

Recall rate of	PSD+SVM	CPT+KL Div.
real hand motion (left or right) vs. rest	99 % / 73 %	93 % / 86 %
real left hand motion vs. real right hand motion	75 % / 76 %	80 % / 75 %
imaginary hand motion (left or right) vs. rest	92 % / 50 %	72 % / 75 %
imaginary left hand vs. imaginary right hand motion	70 % / 72 %	70 % / 56 %

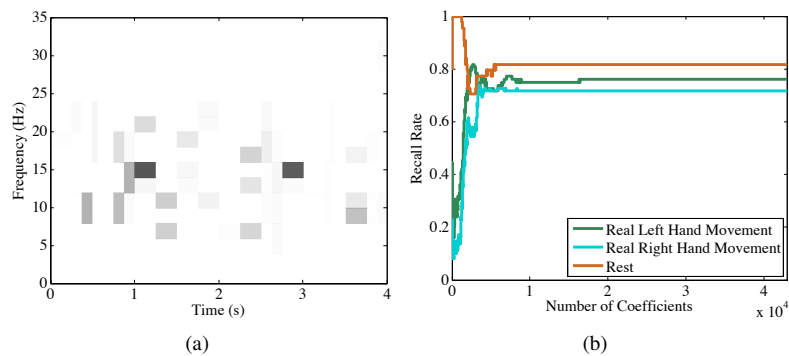


Figure 1: (a) KL Div values for the FCZ channel when discriminating between real right hand movement and rest. For this classification task the FCZ channel was among the ones with the largest KL Div values. Time 0 corresponds to the onset of the visual cue, and high values in the mu- and beta-range may be observed in the following second. (b) Recall rates for a multiclass classification task versus the number of considered basis coefficients.

4. Discussion

We employed the CPT together with a best basis selection algorithm to increase the interclass separability of EEG signals. Our preliminary results indicate that this approach leads to acceptable classification results. However, compared to other algorithms it allows one to detect and interpret the most discriminative channels and time-frequency locations. Let us briefly mention that classifying the best basis coefficients by means of SVM instead of by the least KL Div. led to only minor improvements in recall rates, which supports the use of the best basis algorithm to discriminate between signals.

Acknowledgments

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