Learning Bandpass and Common Spatial Pattern Filters for Motor Imagery Classification

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Abstract

Motor imagery (MI) is a mental process that can be recorded by means of an electroencephalogram (EEG) and produces event-related desynchronization (ERD) and synchronization (ERS) patterns. These patterns exhibit inter and intra-subject variability, which makes models to be trained specifically for each person, requiring long calibration sessions. We introduce a method which can be trained with MI EEGs from different people. We demonstrate with experiments on a public data set that our approach achieves state-of-the-art accuracy on MI EEG classification.

1 Introduction

A brain-computer interface (BCI) is a communication system between the brain and some external device. They are mainly employed in rehabilitation of people with motor impairments, virtual world navigation and control of spelling devices. Among the many mental processes that BCIs can take as input to produce commands to an external device, motor imagery (MI) is one of the most used.

MI is a mental process that consists in rehearsing a movement mentally without any kind of muscular activity as a result [7]. The execution of a MI task produces two kinds of patterns in the electrical activity of the brain. These patterns are called event-related desynchronization (ERD) [11] and event-related synchronization (ERS) [9]. ERD/ERS have both time and frequency domain representations. When recorded in an electroencephalogram (EEG), in the time domain, an ERD represents an amplitude decrease of rhythmic activity in the ongoing EEG signals, and an ERS represents an amplitude increase. In the frequency domain, an ERD/ERS represents a power decrease/increase in certain frequency components within mu (8-13 Hz) and beta (13-30 Hz) rhythms [10].

ERD/ERS can be used to distinguish different MI tasks, however, the identification of these patterns is challenging because, besides the low signal-to-noise ratio, they present inter-subject variability [2], i.e., two subjects can execute the same motor imagery task, but ERD/ERS may happen in different frequency bands, and intra-subject variability [12], i.e., ERD/ERS patterns related to motor imagery can even change over time in the same person, due to factors such as motivation or fatigue [16]. As a result of that, the standard approach is to employ a filter bank [1], that decomposes the EEG signals into multiple frequency bands, and the Common Spatial Pattern (CSP) [6, 3] method for finding spatial filters for each frequency band. Features are extracted after projecting filtered EEG signals into the CSP filters. Then, these features are classified using some machine learning method. However, the effectiveness of CSP depends on the EEG frequency band [4, 8]. Consequently, a wrong choice of the frequency bands in the filter bank may lead to a poor classification performance.

We propose a method based on a deep learning model able to learn suitable bandpass and CSP filters for MI classification. We evaluated the performance of our method on the public data set 2b of the BCI Competition IV [15]. As we will demonstrate, our method not only achieves state-of-the-art accuracy on MI EEG classification, but also it is efficient as it uses only two bandpass filters.

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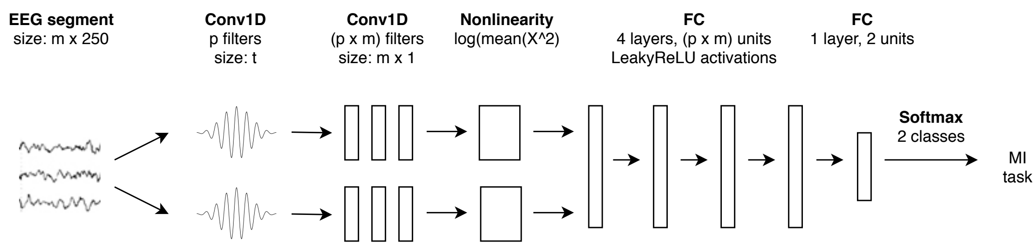

Figure 1: Architecture of our model. It is composed of two 1-D convolutional layers and five fully connected layers all connected sequentially. The input is a tensor of size $m \times 250$, where $m = 3$ is the number of EEG signals. The first 1-D convolutional layer has $p = 2$ kernels of size $t = 125$. The second 1-D convolutional layer has $p \times m = 6$ kernels of size $m \times 1$. The output $x^{(2)} \in I\!R^{6\times 250}$ is reduced to $x^{(3)} \in I\!R^{6}$ after calculating the log-normalized average power of each signal.

2 Our method

Our method is built upon a deep neural network and is composed of 7 layers as illustrated in Figure 1 and the input is an EEG segment $X \in I\!R^{c\times n}$, where c is the number of signals and n is the number of timesamples. The first 1-D convolutional layer is composed of p kernels. The shape of these p kernels is restricted to be defined by the following bandpass filter function:

$$g(t, f_1, f_2) = 2f_2 sinc(2\pi f_2 t) - 2f_1 sinc(2\pi f_1 t)$$

where t represents the number of elements in the filter and $sinc(x) = sin(x)/x$, as in [13]. Hence, the only parameters to be learned are the lower and higher cutoff frequencies f_1 and f_2 respectively, and not all the elements of the filter. Each kernel is applied depthwise, i.e., each EEG signal is convolved with each kernel defined by g. As a result of that, this layer multiplies the number of EEG signals by a factor of p. The second 1-D convolutional layer is composed of $p \times m$ kernels (a set of m kernels for each kernel in the previous layer) of size $m \times 1$, where m is the number of EEG signals. Each kernel represents a CSP filter $f_{csp} \in I\!R^m$. The convolutions of the first and second layers can be seen as the depthwise convolution and 1×1 (pointwise) convolution of a depthwise separable convolution [14, 5]. No activation function is applied to the output of the kernels.

From the output of the second convolutional layers is calculated the average power $\sum_i^n x_i^2/n$ of each EEG signal $x \in I\!R^n$ and normalized using the logaritmic function log_e. These features are feeded to a sequence of 4 fully connected layers (FC) composed of $p \times m$ units each with ReLU activation function. The last FC layer has only 2 units, one for each class of MI task. Finally, the output of the last FC layer is normalized using the softmax function. We used stochastic gradient descent with Adam update rule to minimize the cross-entropy loss function, with a learning rate of 0.1.

3 Experiments and results

We have evaluated our method on the data set 2b of the BCI Competition IV [15]. This data set includes EEGs composed of three signals (from electrodes C3, Cz, and C4) with 4580 trials of two classes of MI tasks (MI of left hand and right hand), from nine subjects with a sampling frequency of 250 Hz. We divided each trial into 1 second windows, obtaining a total of 9160 samples. These samples were divided into training set (8200 samples) and test set (960 samples) maintaining the proportion of trials of each person for both sets.

After testing different architectures with one, two and three kernels in the first layer of our model, we found that two kernels, i.e. two bandpass filters, in the frequency bands of $9.1 - 13.3$ Hz and $13.7 - 18.25$ Hz, are enough to achieve state-of-the-art accuracy of 85.15%, compared to other methods evaluated on the same data set. In addition, our method uses only two frequency bands for classification, that is, less than the average quantity of filters commonly used.

We believe that these frequency bands contain the most reactive components for identifying ERD/ERS of MI. We plan to evaluate our method on other data sets to corroborate our findings.

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