SVM Classification of EEG Signals for Brain Computer Interface.

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SVM Classification of EEG Signals for Brain Computer Interface

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Abstract. In this paper, a brain/computer interface is proposed. The aim of this work is the recognition of the will of a human being, without the need of detecting the movement of any muscle. Disabled people could take, of course, most important advantages from this kind of sensor system, but it could also be useful in many other situations where arms and legs could not be used or a brain-computer interface is required to give commands. In order to achieve the above results, a prerequisite has been that of developing a system capable of recognizing and classifying four kind of tasks: thinking to move the right hand, thinking to move the left hand, performing a simple mathematical operation, and thinking to a carol.

The data set exploited in the training and test phase of the system has been acquired by means of 61 electrodes and it is formed by time series subsequently transformed to the frequency domain, in order to obtain the power spectrum. For every electrode we have 128 frequency channels. The classification algorithm that we used is the Support Vector Machine (SVM).

Keywords. SVM, EEG, classification

Introduction

Brain electrical activity can be easily observed by simply placing a set of wet electrodes on the surface of the head. Every kind of task or thought the human being can perform causes electrical activities in different parts of his/her brain; therefore, the recognition of this activity could be considered as a desirable machine learning application. The task is not so trivial, for many reasons: first, we cannot know the state of all neurons in the brain, but just a mean value of it in some zones of the outer part of the brain. Second, the electrical activity is not limited to a single zone, depending on the task a person is performing: in most cases, it involves the whole brain. The difference among different tasks is mainly in the way electrical waves move from one zone to another. A third problem is that there is always a lot of electrical activity in the brain, also when we are thinking or doing "nothing". This kind of activity, including breathing and all involuntary movements, is always present and can eventually mask the task we intend to monitor. All of this activities represent for us a “noise” that is often bigger than the “signal” we need to detect.

Because of these reasons, the main challenge we are going to face is the classification of the dataset that we collected from the electrodes.

A reasonable classification method for this kind of data relies on artificial neural networks. In this work, we used Support Vector Machines: a tool that is very similar to a neural network, but with the advantage that it can support datasets with a huge number of components; therefore there’s no need of a reduction of the feature space. Moreover, it has a training algorithm that is much better than the “back-propagation” rule usually used in neural networks.

The paper is organized as follow: in the first section we will describe the sensor system, in the second section we will describe the preprocessing that is applied to the acquired data. In third section a description of the classifier is given. In fourth section a description of experimental tests, together with results is shown. Finally we will give a conclusion with some comments and possible improvements for future works.

1. Sensor System

As shown in Fig 1, the recognition system includes three blocks, one for each phase of the signal processing: data acquisition, preprocessing, and classification.

The sensor system is composed of 61 electrodes that are placed at the surface of the head of the subject, according to a standard disposition used in these kind of applications [1,2], as shown in Fig 2.

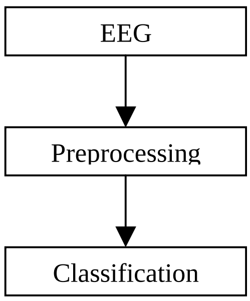

Figure 1. Block-diagram of the sensor system.

Electrodes are connected to the computer by means of fiber optics, in order to provide necessary electrical insulation that guarantee the subject by any risk of electrical shock.

Signals are sampled at a sampling rate of 256 Hz. A picture of the sensor system is shown in Fig. 3.

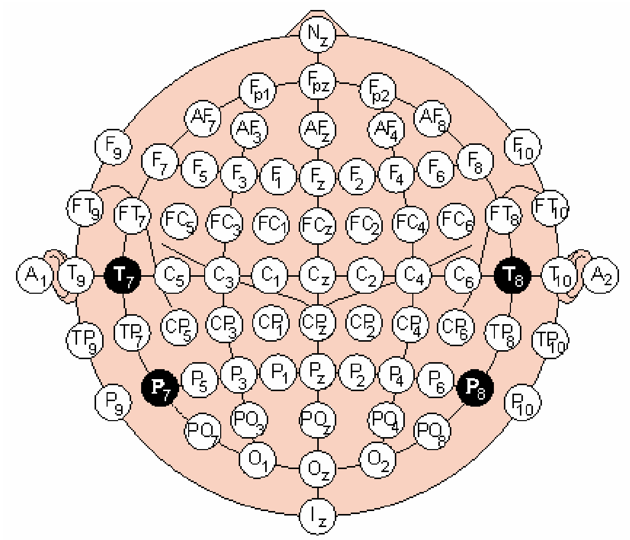

Figure 2. Position and names of the electrodes.

2. Preprocessing

Different types of brain activity are often related to the frequency of the waves that we can find in EEG signals, such as alpha waves (8-12 Hz), beta waves (12-19 Hz), gamma waves (around 40 Hz), delta waves (1-4 Hz) that are associated to weakness, sleep, REM, and other kind of brain states [3-5].

For that reason, we suppose that analyzing the dataset in the frequency domain could be useful for our purpose. For every task, we calculated the FFT in three windows of 256 samples. For each window we get the mean value of alpha waves (8-12 Hz). Of course we considered only the first half of every FFT window, because the second half is symmetric and doesn't give any further information. Channels from 1 to 127 represent frequencies from 1 to 127 Hz. Channel 0 represents frequency 0, and it is omitted.

So, we have a total number of 381 (127 for every one of the three windows) data points for every task that we want to classify. Finally, as there is a great variance in the ranges of the values, we perform a normalization, so that all the values involved we have a range form 0 to 1.

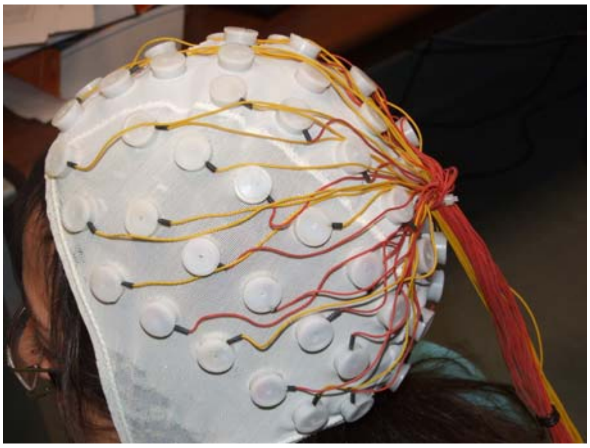

Figure 3. Picture of the sensor system

3. Classifier

In the past few years, SVMs aroused the interest of many researchers being an attractive alternative to multi-layer feed-forward neural networks for data classification and regression or PCA [6,7]. The basic formulation of SVM learning for classification consists in the minimum norm solution of a set of linear inequality constraints. So, it seems useful to exploit the relation between these two paradigms in order to take advantage of some peculiar properties of SVMs: the “optimal” margin of separation, the robustness of the solution, the availability of efficient computational tools. In fact, the SVM learning problem has no non-global solutions and can be solved by standard routines for quadratic programming (QP); in the case of a large amount of data, some fast solvers for SVMs are available, e.g. SVMlight [8]. In the following paragraph we will give a brief description of an SVM.

4. Experiments and Results

In the experiment involved a set of 5 subjects for two days. Every day a subject performed two sessions. During a session, the subject was asked to perform 400 tasks randomly selected among the following: thinking to move the right hand, thinking to move the left hand, performing a simple mathematical operation, and thinking to a carol. Every task lasted three seconds, hence the entire session was 20 minutes long.

Our objective was to operate discriminations between every couple of task: left hand vs. right hand, mathematical operation vs. carol, right hand vs. mathematical operation, left hand vs. carol, right hand vs. carol and left hand vs. mathematical operation. Hence we prepared 6 kinds of datasets, one for every possible combination of the six tasks. The whole datasets was divided in training sets (75% of the datasets) and test sets (25% of the datasets). Accuracy results for training set was always 100%, accuracy results for test set are shown in Table I.

For every subject (denoted with a number, for privacy reason), we performed a mean value of results for 4 different sessions, considered separately, we didn’t mix data from different subjects or different sessions from the same subjects, because they would be to much different. In the table we reported the mean value of the accuracy on the test set, for each subject and every couple of task. In the last line of Table I, we reported mean value for all the subjects.

5. Conclusion

A brain/computer interface is presented, which is able to discriminate among different kind of mental tasks that a subject is performing. It is based on a SVM classifier, which is trained by the power spectrum of the EEG signals coming from 61 electrodes set in the surface of the head.

An experimental test showed quite good results in case of discriminating between the thought of a carol and a mathematical operation, or mathematical operation or carol and hand movements, while results have been very poor in case of discriminating between movement of right hand and left hand. There is a little prevalence of electrical activity in the opposite side of the brain, but this prevalence is not enough to be successfully exploited by the SVM. A greater difference could probably reside in the activation time of the involved areas. Future development will include an analysis in the time domain, in addition to the data considered in this paper. Moreover, we found an high difference in performance according to different subjects: for example, as you can see in the table, with subject 1 we obtained more than 80% in many tasks, while with subject 4 we was just a little over 50%.

Table 1. Accuracy for every task couple.

Subject	Left/Right	Math/Carol	Right/Math	Left/Carol	Right/Carol	Left/Math
1	58%	69%	88%	91%	83%	79%
2	46%	54%	57%	77%	62%	66%
3	55%	58%	77%	73%	71%	77%
4	48%	57%	54%	62%	53%	67%
5	54%	79%	60%	66%	65%	61%
average	52.2%	63.4%	67.2%	73.8%	66.8%	68%

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