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Implementation of Bilinear Separation algorithm as a classification method for SSVEP-based brain-computer interface

Abstract

The aim of this study was to create a two-class brain-computer interface. As in the case of research on SSVEP stimuli flashing at different frequencies were presented to four subjects. Optimal SSVEP recognition results can be obtained from electrodes: O1, O2 and Oz. In this work SVM classifier with Bilinear Separation algorithm have been compared. The best result in the offline tests using Bilinear Separation was: average accuracy of stimuli recognition 93% and ITR 33.1 bit/min, SVM: 90% and 32.8 bit/min.

Keywords: brain-computer interface, SSVEP, Bilinear Separation, Support Vector Machine.

1. Introduction

Brain-computer interface is a multidisciplinary field which merges biomedical engineering, advanced signal processing, artificial intelligence (mostly machine learning) and neuroscience. BCI can be used for direct communication between a brain and a computer, without using muscles. This device is useful for paralyzed people to communicate with surrounding environment [1].

The principle of BCI which uses electroencephalography to measure brain reaction is based on the analysis of evoked potentials. In research presented in this article the Steady State Visual Evoked Potential (SSVEP) was used. This is a signal that is a natural response to visual stimulation at specific frequency. During the stimulation, at the visual cortex of the brain, appears a signal with the same dominant frequency or harmonic components [6]. When there is more than one stimulus on the screen and each flashes at a different frequency, then based on the signal analysis, it could be deduced which of the objects subjected is looking at. SSVEP can be clearly observed in the brain. Its main advantage is that it can be easily classified using classification algorithms.

In this study a very fast and simple Bilinear Separation algorithm was presented in comparison with a well-known algorithm, Support Vector Machine(SVM) [4].

2. Materials and Methods

The high dimensional EEG dataset are collected from SSVEP database [2], [9]. SSVEP acquisition was performed with 128 active electrodes, but in further analyses only three were used: O1, O2 and Oz (according to the international standard of 10-20). Four healthy subjects were told to observe two small reversing black and white checkerboards displayed at 21" CRT computer screen. The checkerboards were flickering at the frequency of 8 and 14 Hz. Signal analysis was carried out in MATLAB. Each dataset contained 5 trials (30 one-second samples for each trial). FFT for signal extraction was used. Features obtained in this way were normalized by scaling between 0 and 1. In further analyses the value of two frequency components: 8 Hz and 14 Hz were used.

In the classifier's learning part recorded samples were used in the five-fold cross-validation test. Full dataset was split into two parts: a test set (120 samples) and a training set with n samples, where $n = 2,...,30$. In each cross-validation fold Bilinear Separation and Support Vector Machines were used. For each of the classifiers the accuracy of the classification was determined.

For SVM a linear kernel was chosen, because it generates the best results. Linear, quadratic, polynomial and Gaussian Radial Basis functions of the kernel were compared. Every one-second sample was registered by three electrodes. The signal from each electrode was analyzed separately. Finally, a result of classification was a value that occurred most frequently. A block diagram of the whole process is presented in Figure 1.

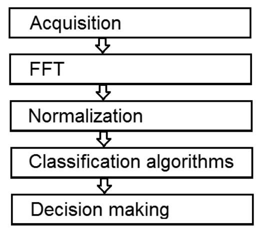

Fig. 1. Block diagram showing the processing steps

3. Bilinear Separation algorithm

Bilinear separation algorithm is described in [5]. In this article, the authors present a new use of this algorithm, which allows a simple classification of features of EEG signal in SSVEP-based brain-computer interfaces.

As opposed to the SVM, which uses two-dimensional data for the separation with a single straight line, the proposed method consists of the separation with a set of two lines. Figures 2 and 3 illustrate the steps of the algorithm. In the first step the two-dimensional data are projected on the abscissa. It is followed by searching for a point x_K on the axis, which separates (with the best accuracy) data into two classes. In the second step, the two-dimensional data are projected on the ordinate and, similarly as before, it is followed by searching for a point y_K on the axis, which separates (with the best accuracy) data into two classes. In that way criterion for classification of samples into two classes is created (K1 and K2):

- for any point $p(x_K, y_K)$, where $x_K \in \langle 0,1 \rangle$, $y_K \in \langle 0,1 \rangle$:

$$\begin{cases} (x < x_K) \wedge (y > y_K) & \text{for } p \in K_1 \\ (x \geq x_K) \wedge (y \leq y_K) & \text{for } p \in K_2 \end{cases} \tag{1}$$

and (x, y) is a coordinate of an intersection point. Points that do not belong to neither of the above ranges were marked as "uncertain". Samples labeled in that way were not classified.

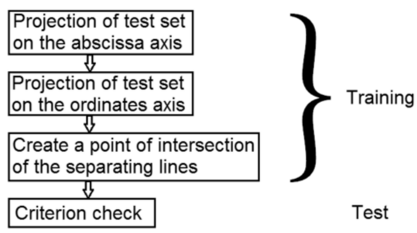

Fig. 2. Block diagram showing the processing steps in bilinear separation algorithm

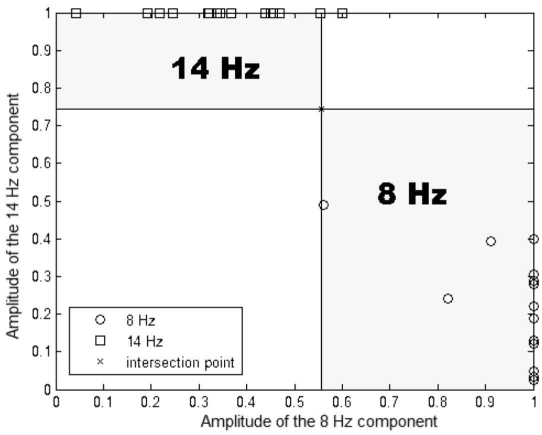

Fig. 3. A method of determining a separating line in bilinear separation algorithm

4. Information Transfer Rate

To describe the overall performance of the BCI system, Information Transfer Rate (ITR) is used. ITR is based on the formula [10]:

$$B_m = \log_2 N + P\log_2 P + (1-P)\log_2\left(\frac{1-P}{N-1}\right)\left[\frac{\text{bits}}{\text{trial}}\right] \quad (2)$$

and:

$$B_t = \frac{60}{T} B_m \left[\frac{\text{bits}}{\text{min}}\right] \quad (3)$$

where P is the classification accuracy, N is the number of targets and T is the time it takes to reach a target. B_m is calculated in bits per trial, B_t is calculated in bits per minute.

5. Results

The results are presented in Figure 4, 5 and 6. Average accuracies of stimulus recognition for each subject are shown in Figure 4. Comparing to SVM, BS algorithm has usually higher accuracy rates in stimulus recognition in small size training sets, but similar in larger training sets. In particular, the case of the Subject 3 shows a significant improvement in the effectiveness of the stimulus recognition. Bilinear Separation algorithm can reject data that is uncertain, hence the difference in the results the two algorithms.

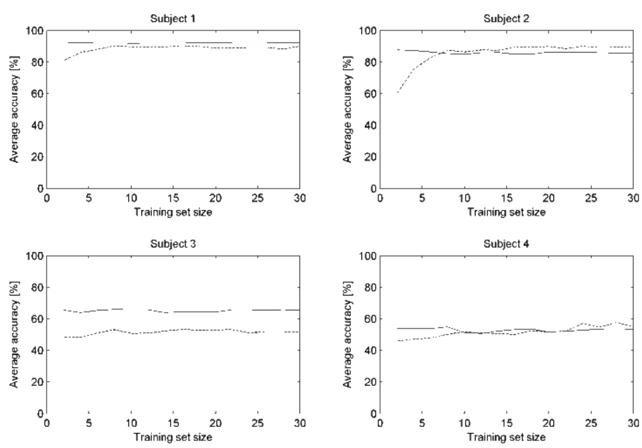

Fig. 4. The average accuracy of stimulus recognition for each subject (SD continuous line, SVM dashed line)

Figure 5 is a presentation of the average accuracy of stimulus recognition depending on the size of the training set. Figure 6 is a presentation of obtained ITR in offline studies depending on the size of the training set. All the results are the average of the results obtained from all four subjects.

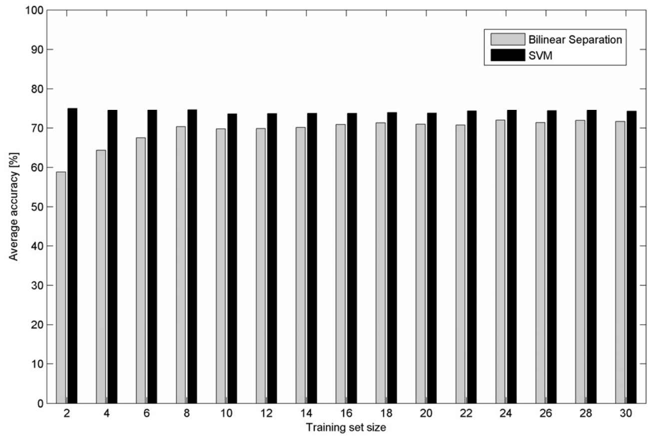

Fig. 5. The average accuracy of stimulus recognition

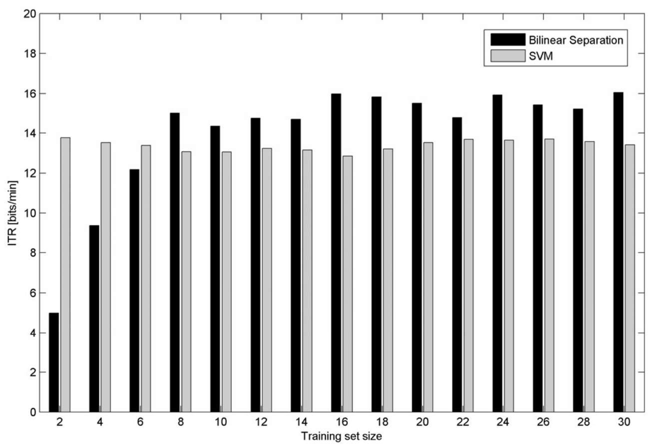

Fig. 6. The average ITR

Bilinear Separation algorithm achieved higher accuracy in stimulus recognition than the SVM. In this case, the size of the training set has little effect on the accuracy. In the case of SVM, accuracy rises to a certain level with the increase of the size of the training set.

The ITR results have also been compared. For smaller data sets Bilinear Separation was better. For larger data sets SVM was slightly better. At the end the amount of time per one sample classification was compared (Table 1). The classification process consisted of: FFT, normalization and computing using one of the algorithms. These results were obtained on a PC with Intel i3 2.53 GHz processor and 4 GB of RAM memory. Short time to make a decision is a great advantage of Bilinear Separation algorithm.

Tab. 1. Comparison of the amount of time per one sample classification

	SVM	Bilinear Separation
with FFT	22 ms	21 ms
without FFT	66 µs	6 µs

6. Conclusions

This study compares two machine learning algorithms used in two-class brain-computer interfaces, based on the analysis of the measured signal in the optical cortex. Well-known classification methods like the SVM were compared with a Bilinear Separation algorithm. The Bilinear Separation algorithm has the best (out of two) accuracy of stimulus recognition and a very satisfactory level of ITR. Furthermore, this algorithm can reject the points that can not be clearly classified into one of the classes. This is the main reason why it is more effective than the other methods of recognition. Unfortunately, it is at the expense of a slightly lower ITR. A significant advantage of this algorithm is a very small computational complexity, thus the algorithm is very fast.

In other studies [10], three two-class interfaces were presented [3, 7, 8]. All of them measured the signal from the occipital areas. Received ITRs were: 2.3 bits/min, 10.3 bits/min, 17.2 bits/min. In this study mean ITR is 12.5 bits/min, but ITR for Subject 1 is 33.1 bit/min, so in comparison to the other ones it is also a good result. Adding more stimuli allows a further increase in the ratio of ITR.

The BS algorithm proposed by the authors can be successfully used in other fields where machine learning is used.

The obtained results are so promising that the authors' future work on brain-computer interfaces will be devoted to the modification of the set of algorithms.

7. References

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