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Classifying EEG Signals in Single-Channel SSVEP-based BCIs through Support Vector Machine

Giovanni Acampora[1], Pasquale Trinchese[1] and Autilia Vitiello[1]

Abstract— **Electroencephalography (EEG) headsets are wearable computing devices capable of recording electrical activity of the brain. These devices play a key role in the Brain-Computer Interfaces (BCIs) systems, i.e., systems capable of acquiring, processing and classifying EEG signals in order to control external devices such as wireless prosthetics. In spite of their crucial role, the current EEG headsets are very uncomfortable being composed of many wet electrodes. Hence, single-channel BCIs with dry electrodes are emerging like wearable devices more accepted by users. Unfortunately, this kind of device typically provides weaker and noisier signal that makes more challenging the classification task. This work is aimed at improving the quality of the classification of EEG signals, and in particular of Steady-State Visual Evoked Potentials (SSVEP), captured by single-channel EEG devices by using an evolutionary algorithm-based optimized version of Support Vector Machine (SVM). As shown by experimental results, the proposed approach improves on the state-of-the-art methods in terms of accuracy.**

I. Introduction

Wearable computing is the study or practice of inventing, designing, building, or using miniature body-borne computational and sensory devices [1]. Applications of wearable computing devices nowadays include a wide range of usages in various industries and environments, which include applications for smart bio-monitoring in health care system, sports training and military operation, and also applications for entertainment, performance art, and improved safety and work efficiency [2]. Among the most interesting wearable computing devices, one can certainty count Electroencephalography (EEG) headsets, namely monitoring devices used to record the electrical activity of the brain.

Brain activity is the result of potential actions of billions interconnected neural cells. Over years, several readout techniques have been developed. Among all of them, EEG, applied for the first time by Hans Berger in 1929 [3] and improved more and more over the years thanks to the advances in technologies, represents one of the most valid and least invasive method, besides its inexpensiveness and high temporal resolution [4]. In detail, EEG signals can be captured by means of headsets composed of a set of electrodes placed in an array along the subject's scalp. These devices play a key role in the so-called Brain-Computer Interfaces (BCIs) systems, i.e., systems capable of acquiring, processing and classifying brain signals in order to control an external device [5] such as wireless prosthetics. Indeed, this technology has become crucial in helping people with physical disabilites, acting as a communication channel with the outside environment. However, BCIs can also be useful to healthy subjects providing them new ways to interact with computers and other devices for example in video games [6] [7] [8] and entertainment applications [9] [10].

Unfortunately, in spite their crucial role, the current EEG headsets are affected by a weakness: they are very uncomfortable to use in the everyday life because of the use of many electrodes, typically wet, i.e., covered by a conductive gel such as a saline fluid (necessary to improve the signal quality). Hence, nowadays, the highest human computer interaction (HCI) challenge of wearable devices is physical interactivity in the face of social acceptance [11]. In order to address these challenges, there is a strong interest in developing single-channel BCIs with dry electrodes. Indeed, in this case, the used wearable headset is composed of few electrodes uncovered by fluid gel. However, if, on one hand, this kind of EEG headset is more comfortable, it leads to another challenge: to obtain an accurate EEG signal classification. This challenge is due to the fact that the exploitation of few electrodes leads to collect little data to be processed. Moreover, dry electrodes typically provide weaker and noisier signals.

Our research activities put efforts in developing machine learning based approaches to improve the classification quality of EEG signals captured by wearable single-channel headsets. In particular, our research focuses on the so-called Steady-State Visual Evoked Potentials (SSVEPs), a category of EEG signals, that have been widely applied because of their little training requirements [12]. More precisely, SSVEP signals are synchronous responses to a periodic visual stimulus. The most affected brain region is the visual cortex area, where signals with the same frequency as that of the stimuli, flickering lights or images, can be captured by EEG electrodes. In this work, we apply the Support Vector Machine (SVM) to classify SSVEP signals captured by a single-channel EEG headset. Over years, SVM has emerged as a powerful technique for classification. However, one of the central open questions is the model selection [13]: how does one tune the parameters of the SVM algorithm to achieve optimal generalization performance? To answer this question, we apply an evolutionary algorithm based approach to perform the SVM's model selection. The proposed approach has been evaluated in an experimental session where EEG signals from eleven volunteers have been used. As shown by results, our proposal outperforms on state-of-the-

[1]Giovanni Acampora, Pasquale Trinchese and Autilia Vitiello are with the Department of Physics "Ettore Pancini", University of Naples Federico II, 80126 Naples, Italy {giovanni.acampora, pasquale.trinchese, autilia.vitiello}@unina.it

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art approaches in terms of accuracy.

The paper is divided as follows. In Section II, the state-of-the-art approaches related to our work are reported. In Section III, a detailed description of our system is provided. The experimental setup is described in Section IV together with the obtained results. We finally conclude the paper in Section V.

II. Related work

Machine learning techniques, including linear classifiers, neural networks, nearest neighbour classifiers and their combinations [14], have been widely applied for classifying multi-channel BCI signals. In the most part of this research, the signal feature extraction is performed by the Fast Fourier Transform (FFT), which is a well-known algorithm to extrapolate frequency information from a signal in the time domain. For example, Muller et al. [15] adopted this method to control an electrical prosthesis, with accuracies ranging from 44% to 88% and response time between 2 - 5 seconds, using a 4-channel BCI. A similar approach was used by Po-Ley et al. [16] to design a single channel BCI gaming system, reaching an accuracy of 96% with 2 seconds response time for the classification of two-classes signals. For this reason, in our approach, we use this kind of feature extraction procedure. As for SVM, it has been widely applied in the multi-channel BCI systems. Examples of uses of SVM can be found in [17] [18] [19] with promising results. Moreover, in literature, there are some applications of SVM in single-channel BCI systems for classification of P300 signals [20] and motor imagery EEG signals [21].

Starting from these results, in our work, we decided to apply the SVM to classify SSVEPs captured by single-channel EEG devices. To the best of our knowledge, only few efforts have been carried out in applying machine learning algorithms for classifying SSVEPs in single-channel BCI systems. In detail, in [22], Linear Discriminant Analisys (LDA) is presented for classifying four stimuli SSVEP data. Moreover, for a similar task, Logistic Regression (LR) is applied in a very recent paper [23]. Hence, the goal of the paper is to show the benefits of the SVM application in classifying SSVEPs in single-channel BCI systems with respect to the state-of-the-art approaches such as LDA and LR.

III. Our Proposal

This paper aims to improve the classification accuracy of SSVEPs signals obtained with a single-channel EEG-BCI device. In particular, we applied the Support Vector Machine (SVM) as classification technique, by using an Evolutionary Algorithm (EA) for the problem of the model selection, as explained in this section. The concept design of the developed system is shown in Fig. 1. A *stimulating platform* provides visual stimuli to the subject. Brain signals are captured by a *single-channel EEG data acquisition headset* and, finally, sent to a *processing unit* responsible for the analysis of the digitized data, extraction of the relevant features and classification of the observed stimuli. The mentioned components are described in details below.

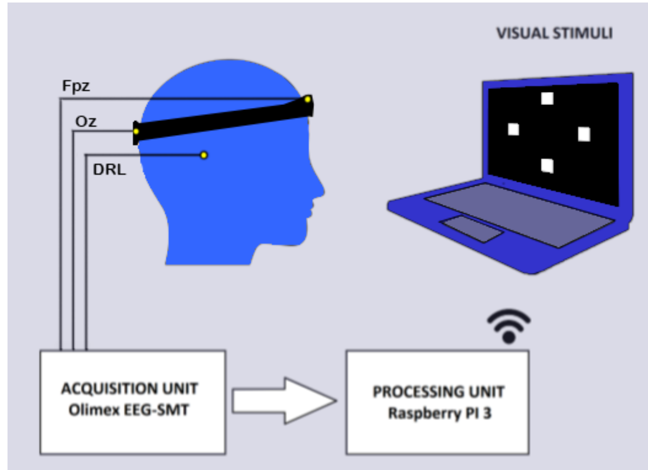

Fig. 1. Architecture of the SSVEP-based BCI system.

A. Stimulating platform

The stimulating platform provides the visual stimuli and consists of a 15.6” laptop monitor, 60 Hz refresh rate. The stimuli are black-white squares, 80x80 pixels, oscillating on a black background each with a frequency compatible with the monitor refresh rate [24].

B. Acquisition unit

Brain signals are captured by using two active dry electrodes (see Fig. 2) placed at the Fpz and Oz positions, according to the international 10-20 system [25], and a passive electrode positioned on the earlobe, known as Driven Right Leg (DRL). The Oz electrode has been modified by adding gold plated pins for a better contact with the scalp through the hair. The three electrodes are embedded in a self made 3D-printed headset and form a single BCI channel. Signals are digitized through the Olimex EEG-SMT, a two channel differential input 10-bit analog-digital converter (ADC) with a sampling frequency of 256 Hz and finally sent to the processing unit. The headset and the Olimex device are shown in Fig. 3. The whole system is battery powered, with an expected autonomy of three hours.

Fig. 2. Fpz electrode and the modified Oz electrode.

(a)

(b)

Fig. 3. (a) The 3D printed headset; (b) the Olimex EEG-SMT acquisition device.

C. Processing unit

The processing unit is represented by a Raspberry Pi 3 single-board computer. It is devoted to process EEG signals and perform two main tasks: the feature extraction and the classification.

1) Feature extraction: Firstly, the processing unit is responsible for the extraction of the relevant features. Starting from the original EEG track, several overlapping segments of fixed length are selected. The length of the segments is defined as the *time window length* while the *overlap* defines the portion of signal shared by two successive segments. Then, each segment is converted from the time domain to the frequency domain using the Fast Fourier Transform (FFT) [26], whose numerical expression is given by:

$$X_q = \sum_{k=0}^{N-1} x_k e^{-i\frac{2\pi kq}{N}} \tag{1}$$

where $x_0, ..., x_{N-1}$ are the elements of the input buffer, N its length, and $X_0, ..., X_{N-1}$ are complex numbers constituting the transformed signal. The power spectrum of the FFT within 4 Hz and 32 Hz is used as feature vector.

2) Signal classification: The obtained signal segments are firstly standardized such that the feature vectors have zero mean and unit variance. Then the classification has been carried out by using the Support Vector Machine (SVM). SVM is a binary classifier that finds an optimal hyperplane by separating each class in a high dimensional mapping of the features space [27]. In detail, given a set of labeled training instances $(\mathbf{x}_1, y_1), ..., (\mathbf{x}_l, y_l)$ with $\mathbf{x}_i \in \mathbb{R}^n$ and $y_i \in \{-1, 1\}$, SVM requires the minimization of

$$\frac{1}{2}\mathbf{w}^2 + C\sum_{i=1}^{l}\xi_i \tag{2}$$

subject to the constraints

$$y_i(\mathbf{w} \cdot \phi(\mathbf{x}_i) + b) \geq 1 - \xi_i \tag{3}$$

$$\xi_i \geq 0 \tag{4}$$

where $\phi : \mathbb{R}^n \rightarrow \mathbb{R}^N$ is a vector function that maps the n-dimensional input vector $\mathbf{x}$ into an N-dimensional feature vector and can be defined by a kernel function $K(\mathbf{x}_i, \mathbf{x}_j) = \phi(\mathbf{x}_i)^T\phi(\mathbf{x}_j)$. C is the penalty parameter (also known as regularization parameter).

Some common kernels are:

- $K(\mathbf{x}_i, \mathbf{x}_j) = \mathbf{x}_i^T\mathbf{x}_j$ (linear)
- $K(\mathbf{x}_i, \mathbf{x}_j) = (\gamma\mathbf{x}_i^T\mathbf{x}_j + r)^d$ (polynomial)
- $K(\mathbf{x}_i, \mathbf{x}_j) = \exp(-\gamma|\mathbf{x}_i - \mathbf{x}_j|^2)$ (radial basis function)

As kernel function we choose the radial basis function (RBF), proved to have the best performances in literature [28] [29] [30].

The SVM model has been optimized and trained separately on a high performance computer and sent back to the processing unit for its operation. The optimization step has been carried out by applying an evolutionary approach, and, in particular, a genetic algorithm. Genetic algorithms try to solve an optimization (or search) problem by manipulating a population of potential solutions and by reproducing the Darwinian natural evolution which leads to the survival of the only fittest individuals capable of adapting to the changing environment [31]. Precisely, they operate on encoded representations of the solutions, called chromosomes. In our case, the chromosome is represented as a real vector composed of the SVM parameters to be tuned. In detail, the parameters tuned for the SVM classifier are the penalty parameter C, the γ parameter related to the RBF kernel function $K(\mathbf{x}_i, \mathbf{x}_j) = \exp(-\gamma|\mathbf{x}_i - \mathbf{x}_j|^2)$, described above. The SVM individual is then of the form (C, γ). Initially, a population of individuals, in our case of 50 individuals, is randomly created by considering a range of values for each SVM parameter. Then, the algorithm evolution continues with successive generations. In each generation, the following steps are performed: evaluation, selection, recombination and mutation. During the evaluation, each solution is evaluated by means a fitness function that reflects how good it is, compared with other solutions in the population. In our case, the fitness value of a chromosome is the average accuracy calculated by applying a ten-fold cross-validation procedure where the SVM model trained by considering the parameters contained by the chromosome is used. Then, by means of a selection mechanism, parents of the population of the next generation are selected. The parents are undergone to the crossover and mutation operators to create the new population. In particular,

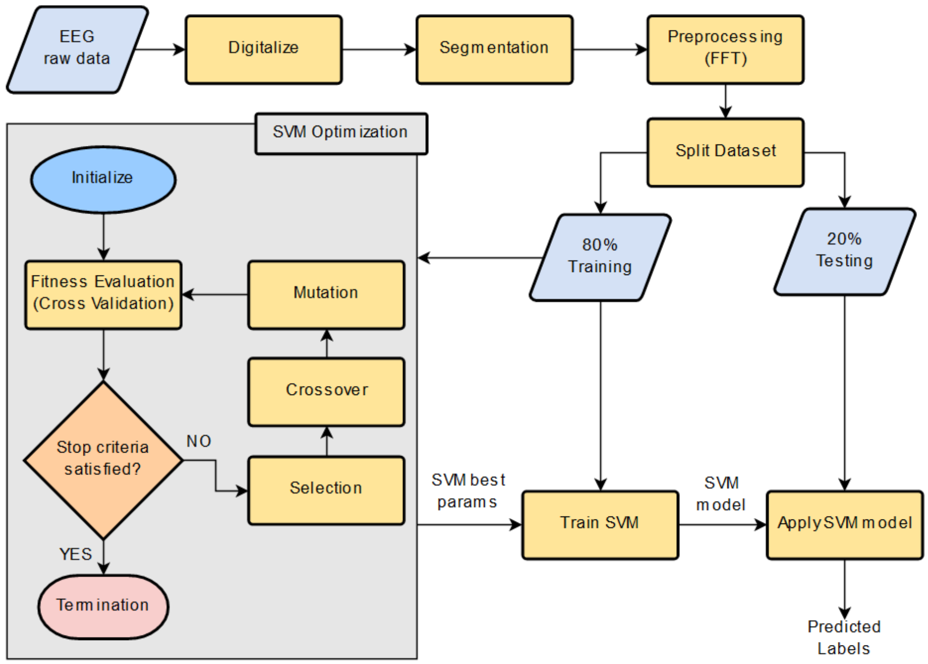

Fig. 4. Data processing flowchart of the single channel EEG system.

crossover exchanges portions between two randomly selected chromosomes and mutation causes random alteration of the chromosome components. In our case, the genetic operators applied in each generation are the one-point crossover and the polynomial mutation, with 5% independent probability for each parameter to be mutated. The algorithm evolution terminates when specified conditions such as the maximum number of generations are reached. In our case, we consider 1000 generations as termination condition.

The whole process, from data acquisition to the classification, is summarized in Fig. 4.

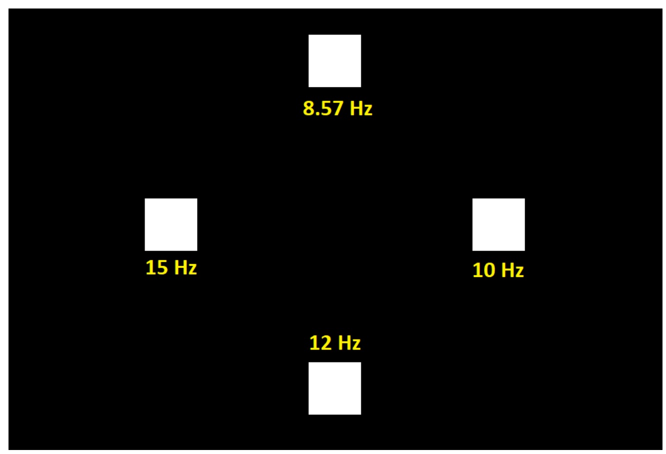

Fig. 5. Visual stimuli window showing the disposition of the four flickering squares [23]

IV. Experiments and Results

This section is devoted to show the benefits provided by the proposed approach with respect to the state-of-the-art methods. In order to achieve this aim, firstly, a detailed description of the created dataset, the experimental setup and the performance measure is provided. Then, the results of the experiment are discussed in a deeper way.

A. Dataset creation and description

The dataset was built by enrolling eleven volunteers, aged from 25 to 50 years. Volunteers were positioned, one by one, at 70 cm away from the stimulating platform (see sec. III-A) and equipped with the data acquisition headset. The chosen stimuli are four 80x80 pixel squares, alternating between black and white at the frequencies 8.57 Hz, 10 Hz, 12 Hz and 15 Hz respectively, on a black background (Fig. 5). The procedure followed by each participant is:

- For each frequency,
  - Focus on the corresponding square for 16 seconds.
  - Wait 4 seconds.

This way we obtained 44 recordings of 16 seconds each, for a total of 704 seconds of data.

The raw dataset was processed as explained in section III-C.1. In our previous work [23], EEG signals were segmented in different time window lengths, precisely $2s, 3s, 4s, 5s, 6s$, using six overlap percentage ranging from 35% to 95%. Here, we make use of the same time windows keeping the value 95% for the overlap, which provided the best results. Since both the dataset and the FFT sizes depend on the time window, for sake of completeness, we report in Table I the number of instances and the length of the feature vectors for each time window length.

TABLE I

NUMBER OF FEATURES AND INSTANCES FOR EACH TIME WINDOW SIZE.

Window	# Features	# Instances
2.0 s	56	7020
3.0 s	84	4673
4.0 s	112	3500
5.0 s	140	2796
6.0 s	168	2327

B. Experimental setup and performance measures

The dataset was first partitioned into two subset: 80% for training and 20% for testing. The training dataset has been used for the optimization of the hyper-parameters of SVM using the classical ten-fold cross-validation during the fitness function running of the implemented genetic algorithm. The best parameters reached by the genetic algorithm for each time window are shown in Table II. The remaining 20% testing dataset has been finally used to validate the trained model.

TABLE II

BEST SVM PARAMETERS ACHIEVED BY THE EVOLUTIONARY ALGORITHM

Window	C	γ
2.0 s	59	3.1e-3
3.0 s	689	2.5e-3
4.0 s	28	1.9e-3
5.0 s	79	2.9e-3
6.0 s	187	4.6e-3

The measure used to evaluate the proposed algorithms is the well-known *accuracy* metric, defined as the ratio of correctly predicted classes to the total number of predictions made, i.e.:

$$accuracy = \frac{n\_correct\_prediction}{n\_total\_prediction.} \tag{5}$$

The results in terms of the accuracy of the proposed SVM have been compared with the results of the state-of-the-art approaches for single-channel EEG signal classification, namely LDA [22] and LR [23], obtained on the same dataset and reported in the work [23].

C. Results

Table III shows the accuracy scores of all compared methods on testing datasets against the considered time window lengths, whereas, Table IV shows the relative improvements of the proposed approach with respect to the state-of-the-art methods. Looking at the two tables, it is possible to say that the proposed approach outperforms the state-of-the-art methods by taking into account all considered time window lengths. In addition, the amount of the improvement is remarkable. Indeed, the proposed approach have an average improvement of 16.9% and 11.8% on LDA and LR, respectively. By analysing the improvements in Table IV, it is worth noting that the amount of the improvement is lower for high time windows. This is due to the fact that there is a large amount of information to perform the classification when higher lengths of the time window are considered. Therefore, in this case, also LDA and LR succeeds to obtain good performance by reducing the amount of improvements of the proposed approach. However, in order to reach a real time classification, the desirable thing is to use lower length of the time window. So, this analysis shows that our proposal is more adequate to reach a real time classification for single-channel EEG signals with respect to the state-of-the-art approaches.

TABLE III

ACCURACY ON TESTING DATA FOR THE COMPARED CLASSIFIERS

Window	LDA	LR	SMV
2.0 s	59.4%	58.8%	74.5%
3.0 s	69.6%	73.8%	85.4%
4.0 s	76.3%	81.7%	92.7%
5.0 s	89.2%	93.3%	95.6%
6.0 s	90.7%	96.9%	97.6%

TABLE IV

RELATIVE IMPROVEMENTS OF THE PROPOSED APPROACH

Window	LDA	LR
2.0 s	25.4%	26.7%
3.0 s	22.7%	15.7%
4.0 s	21.5%	13.5%
5.0 s	7.2%	2.5%
6.0 s	7.6%	0.7%
Average	16.9%	11.8%

V. CONCLUSIONS

This paper presents the use of an SVM classifier for a single-channel SSVEPs-based BCI system. As shown from the experimental results, the proposed approach outperforms the performance of state-of-the-art approaches, especially by considering small lengths of time windows where capturing the signal. This is a remarkable side-effect that shows that our proposal is more suitable for addressing real time classification of single-channel EEG signals with respect to the state-of-the-art approaches. In the future, new efforts for improving the proposed approach could be made by applying different evolutionary algorithms to enhance the model selection procedure. Moreover, other machine learning approaches such as neural networks could be applied for addressing the single-channel EEG signal classification.

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