Adoption of Machine Learning Techniques to Enhance Classification Performance in Reactive Brain-Computer Interfaces

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***Abstract*—This paper proposes the adoption of an innovative algorithm to enhance the performance of highly wearable, reactive Brain-Computer Interfaces (BCIs), which exploit the Steady-State Visually Evoked Potential (SSVEP) paradigm. In particular, a combined time-domain/frequency-domain processing is performed in order to reduce the number of features of the brain signals acquired. Successively, these features are classified by means of an Artificial Neural Network (ANN) with a learnable activation function. In this way, the user intention can be translated into commands for external devices. The proposed algorithm was initially tested on a benchmark data set, composed by 35 subjects and 40 simultaneous flickering stimuli, obtaining performance comparable with the state of the art. Successively, the algorithm was also applied to a data set realized with highly wearable BCI equipment. In particular, (i) Augmented Reality (AR) smart glasses were used to generate the flickering stimuli necessary to the SSVEPs elicitation, and (ii) a single-channel EEG acquisition was conducted for each volunteer. The obtained results showed that the proposed strategy provides a significant enhancement in SSVEPs classification with respect to other state-of-the-art algorithms. This can contribute to improve reliability and usability of brain computer interfaces, thus favoring the adoption of this technology also in daily-life applications.**

***Index Terms*—Augmented Reality, Brain-Computer Interface, EEG, Health 4.0, Instrumentation, Machine Learning, Neural Networks, SSVEP, Real-Time Systems, Wearable Systems.**

I. Introduction

The widespread diffusion of Brain-Computer Interfaces (BCIs) is bringing significant improvements in human-machine interaction. A BCI, in fact, is a technology able to provide a direct communication path between human brain and external devices [1]. Depending on the extracted information and techniques, BCIs fall under three different categories such as active, reactive, and passive systems [2]. In particular, reactive BCIs are characterized by acquisition and processing of brainwaves produced in response to external stimuli. Among all the reactive-BCI paradigms, Steady-State Visually Evoked Potentials (SSVEPs) have been successfully employed for applications regarding healthcare [3], entertainment [4], and industry [5]. SSVEPs are elicited in the primary visual cortex when users observe a flickering stimulus, usually in the range 6-30 Hz. Typically, the brain response is a sinusoidal-like waveform with a fundamental frequency equal to that of the observed flickering stimulus. However, most often, higher harmonics can also be detected [6].

A set of N flickering stimuli at different frequencies can be associated to specific commands, so that the user can select the desired target by simply looking at the corresponding flickering stimulus. Traditionally, these stimuli are displayed on LCD monitors. Moreover, a multi-channel EEG acquisition is often required [7]. This setup represents the best practice to obtain satisfying performance, but it is also bulky and limits the portability of these systems. Recently, wearable solutions have been proposed in order to facilitate the adoption of BCI-SSVEP in daily applications. These systems are based on single-channel electroencephalographic (EEG) acquisitions [8] and, most notably, they resort to the use of Augmented Reality (AR) devices to render the flickering stimuli [9]. However, the overall performance of such integrated AR-BCI systems strongly depends on the specifications of the chosen AR device. Indeed, two main issues can be highlighted. First, the field of view (FOV) of these devices is generally limited to some tens of degrees: this inevitably limits the maximum number of flickering stimuli to be simultaneously rendered. Secondly, AR devices are less powerful than laboratory desktop PCs: hence, significant frame rate variations can occur when the AR-BCI application is running. In particular, the latter contribution leads to a shift in the values of the rendered frequencies and, therefore, to a degradation of the classification performance of the detected SSVEPs [10]. For this reason, one of major challenges is to reach the state-of-the-art results [11] also with wearable equipment. To this aim, Machine Learning (ML) classifiers represents a promising strategy [12]. In fact, several works have addressed the use of Support Vector Machine (SVM), k-Nearest Neighbors (k-NN) [13], [14], and Neural Networks (NNs) [15], [16], by significantly improving the performance.

On the basis of these considerations, in this work, the classification performance of highly-wearable BCIs is improved by adopting an innovative algorithm which, after a features extraction of the acquired signal, employs an Artificial Neural Network (ANN) to classify them and translate the user's gaze into a command. With respect to traditional ANNs, a variable activation function (VAF) is adopted [17] to further improve the classification capability of such classifier. In the first phase, the proposed algorithm was tested on a benchmark data set [11], composed by 35 subjects and 40 simultaneous flickering stimuli. Successively, it was also applied to a data set obtained by using highly wearable BCI equipment and involving 20 subjects [3], [10]. Finally, the obtained results were compared with the state of the art.

The paper is organized as follows. Section II describes the proposed ML-based algorithm. Therefore, the validation on a benchmark data set is addressed in Section III. Further results on a data set obtained through the aforementioned highly-wearable setup are discussed in Section IV. Finally, in Section V, conclusions are drawn.

II. The Proposed Algorithm

The proposed algorithm is described in Fig. 1. Given a *Stimuli Platform* used to render an arbitrary number N of flickering stimuli, the user *EEG SSVEP* is processed by means of the *SSVEP features extraction* block, in order to reduce the dimensionality of the acquired samples, without losing important information. Finally, the resulting features are normalized and classified by the *Features Classification* block, by means of the implemented *VAF ANN*, which eventually provides information regarding what visual stimuli the user has gazed.

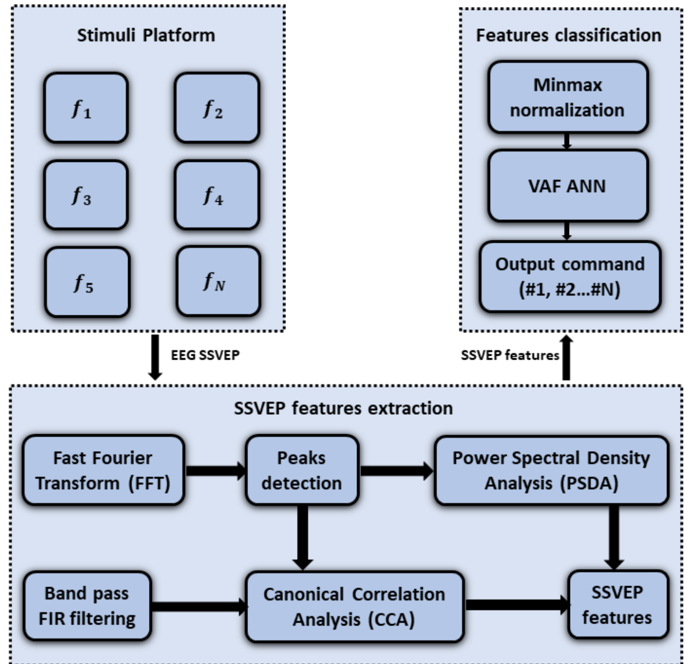

Fig. 1. Architecture of the proposed algorithm for the classification of SSVEPs.

A. Features Extraction

The features extraction block adopts a combined processing in time and frequency domains.

- *Frequency domain:* first, an FFT of the user's EEG is performed. Then, the actual SSVEPs *Peaks* are detected in the neighbours of all the N stimulus frequencies. Finally, the Power Spectral Density Analysis (*PSDA*) around the detected peaks provides N coefficients $P_1, P_2, ..., P_N$, which constitute the frequency-domain features.
- *Time domain:* first, the acquired EEG is filtered by means of a *Band pass filtering* by adopting a Finite Impulsive Response (FIR) filter between 9 and 25 Hz. Successively, the Canonical Correlation Analysis (*CCA*) between the filtered signal and a set of sinewaves, having the frequencies of the N detected peaks and variable phase, is performed. Finally, a number N of CCA coefficients $\rho_1, \rho_2, ..., \rho_N$ are obtained, and constitute the time-domain features.

In this way, for each brain signal composed of $f_s \cdot n$ samples and N classes (where f_s is the sampling frequency, n is the number of seconds, and N is the number of stimulus frequencies), only $2N$ features are extracted.

It is worth mentioning that the Peaks detection block is implemented with the aim to mitigate the uncertainty introduced by the AR devices during the generation of the flickering stimuli. For the sake of example, an fps variation from 60.0 Hz to 58.0

TABLE I
OPTIMIZED HYPERPARAMETERS AND VARIATION RANGES

Hyperparameter	**Range**
Fixed Activation Function	{ReLU, Tanh}
Hidden Layer Neurons	[5, 505] step: 50
VAF Layer Neurons	{3, 7, 11}
Learning Rate	{0.0005, 0.0001, 0.0010, 0.0050, 0.0100}
Validation Fraction	{0.2, 0.3}

Hz inevitably leads to a shift of the rendered frequencies from 12.0 Hz to 11.6 Hz. Hence, an adaptive strategy can provide more accurate values of PSDA and CCA coefficients, resulting in a more effective classification of the user SSVEPs.

B. Features Classification

The classification is performed by the *Features classification* block. First, the $2N$ features are normalized by a *Minmax* normalization. Then, an Artificial Neural Network with a Variable Activation Function (*ANN VAF*) is implemented for the classification phase, aiming to provide an *Output command* related to the user's gaze. A traditional ANN is a Feed-Forward Artificial Neural Network where one or more layers of hidden neurons can be used between the input and output layers. Each layer is connected with the previous and the next one with weighed connections W, so that the sample propagation occurs forward, without loops or cross connections. In the learning phase, an error function $E(W)$ is minimized through a proper learning algorithm such as *Gradient Descent*. With regard to the ANN VAF technique [17], it consists of a traditional ANN model with trained activation functions, which are expressed in terms of sub-networks with one hidden layer. Therefore, this further one-hidden-layer neural network can enable the resulting activation functions of ANN layers to assume any shape.

C. Validation

Typically, SSVEPs are characterized by huge inter-individual variability [18]. Hence, a suitable approach to validate the proposed algorithm is the Leave-One-Subject-Out Cross Validation (LOSO CV), which is a variant of the K-fold cross-validation. In fact, given a number M of subjects, LOSO CV procedure divides the entire data set in M folds, where each fold is constituted by a specific subject. Therefore, for each combination of the models hyperparameters, the process will run M times, each time with a different subject in the test set, taking the remaining $(M-1)$ in the training set. Table I shows the adopted grid search for the tuning of the ANN VAF hyperparameters. Two metrics are used to evaluate the classification performance: (i) classification accuracy, and (ii) acquisition time. The classification accuracy is defined as the percentage of brain signal correctly classified, while the acquisition time represents the time duration of the signals considered.

TABLE II
CLASSIFICATION ACCURACY WITH A 5-S ACQUISITION TIME

Method	**Accuracy (%)**
Proposal (FE + VAF ANN)	**95.5 $\pm$ 3.8**
1D SSVEP Convolutional Unit [19]	68.6
PodNet [19]	86.2
Filter Bank CCA [19]	97.9

III. PRELIMINARY VALIDATION ON BENCHMARK DATA SET

The proposed algorithm was tested on a Benchmark data set proposed by *Wang et. Al* in [11]. The obtained results are compared with those obtained by other state-of-the-art processing strategies.

A. Data Description

The considered benchmark data set involved 35 healthy subjects (17 females and 18 males, aged 17–34 years, mean age: 22 years), with normal or corrected-to-normal vision. Among them, 8 subjects had previous experience in SSVEP-based BCI. An offline BCI speller using 40 flickering targets was designed. These stimuli were presented on a 23.6-in LCD monitor (Acer GD245 HQ, response time: 2 ms) with a resolution of 1920 $\times$ 1080 pixels, and a refresh rate of 60 Hz. The viewing distance from the screen was 70 cm. A sampled sinusoidal stimulation method was applied to present visual flickers on the LCD monitor. The chosen frequencies were in the range [8.0-15.8] Hz with a 0.2 Hz step. A *Synamps2* EEG acquisition unit (Neuroscan, Inc.) and 64 electrodes were used to record EEG data at a sampling rate of 1 kSa/s.

For each volunteer, the experiment included six blocks. Each block was composed of 40 trials, corresponding to all 40 squares to be gazed at, one at the time, for 5 s. A rest for several minutes between two consecutive blocks was foreseen.

B. Results and Discussion

The obtained experimental results, considering a 5-s acquisition time, are shown in bold in Table II along with a comparison with other state-of-the-art techniques [19]. The classification accuracy and corresponding inter-individual 3-σ uncertainty is also reported. The selected channels were PO8, PO7, PO6, PO5, PO4, PO3, POz, O2, O1, and Oz. As visible, the proposal outperforms both the *Podnet* and the *1D SSVEP Convolutional Unit*. However, *Filter Bank CCA* reaches an accuracy greater of about 2%. This method is confirmed to be the best processing strategy to be adopted for traditional setups, based on multi-channel acquisition and LCD displays, which have a negligible frame-per-second variation. As a consequence, in this case, the *Peak detection* block does not provide significant improvement. On the other hand, the proposed approach is very promising when the frame rate is more unstable, which is the case with highly wearable, AR-based setups.

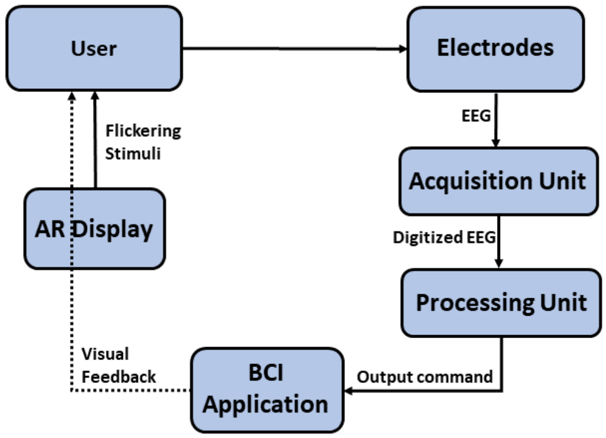

Fig. 2. Major blocks of the system architecture.

IV. Validation on a Wearable SSVEP-BCI System

After the preliminary test on a benchmark data set, the proposed algorithm was applied to a data set obtained by adopting a highly-wearable SSVEP-based BCI, developed by the Authors in [3], [5]. Finally, the obtained results are compared with the CCA technique.

A. Architecture

The system architecture is shown in Fig. 2. An *AR Display* renders N flickering stimuli for the SSVEPs elicitation. Then, only three dry *Electrodes* are placed in *Oz*, *Fz*, and *A2* positions according to the 10-20 International System [3], and capture the user EEG. The brain signal is acquired by a portable *Acquisition Unit*, which sends the digitized EEG samples to a portable *Processing Unit*. The processing unit runs the proposed SSVEP classification algorithm, and sends in real time the output command to the *BCI Application*, which actuates the received command (which can be, for example, to display some AR content as a *visual feedback*).

B. Hardware

The AR device chosen was the *Epson Moverio BT-200*. It is an Optical-See-Through device with a 23° diagonal field of view, and a nominal refresh rate of 60 Hz. The selected acquisition unit was the Olimex EEG-SMT, a 10-bit, 256 S/s, open source Analog-to-Digital converter. Finally, the adopted processing unit was the Raspberry Pi 4, a single-board PC connected via USB to the Olimex.

C. Software

The generation of the flickering icons on the Epson Moverio glasses was implemented by using Android Studio. The AR environment consisted of two squares placed at opposite edges of the screen. Each square reverses black and white according to the chosen flickering frequency. Moreover, a software written in Python 3 was used to (i) acquire the digitized signal via USB from the acquisition unit, (ii) process it by means of the *Scikit-learn* tool, and (iii) send the output command to the specific target via TCP/IP [3], [9], [10]

TABLE III
Classification Accuracy and Corresponding Inter-Individual 3-σ Uncertainty

T (s)	CCA [3] (%)	VAF ANN (%)
0.5	70.8 ± 5.0	75.0 ± 4.7
1.0	74.8 ± 9.1	82.2 ± 4.9
2.0	84.9 ± 6.1	89.1 ± 3.9
3.0	91.0 ± 4.7	93.8 ± 2.6
5.0	95.4 ± 2.8	96.7 ± 2.1
10.0	-	99.4 ± 1.4

D. Data Description

An experimental campaign involving 20 healthy adult volunteers was conducted to evaluate the performance of the proposed algorithm. The flickering frequencies chosen were 10 Hz and 12 Hz. 24 brain signals per subject were acquired. For each trial, each volunteer was asked to stare at the selected stimulus for 10 s. A resting phase of approximately 10 s was foreseen between two consecutive trials.

E. Results and Discussion

Table III summarizes the classification accuracy achieved by the proposed algorithm, compared with that obtained through the CCA adopted in [3]. As visible, the enhancement provided is significant for each of the acquisition time T considered. One of the main contribution to this improvement is certainly given by the *Peak Detection* block, which allows to obtain more accurate features both in time and frequency domains, since the uncertainty caused by unpredictable fps variation of the Epson Moverio BT-200 is mitigated. Currently, this adaptive strategy to find the FFT peak position and extract appropriate features represents the most reliable solution to improve the SSVEP classification in AR-based setup. Finally, it can be also seen that the CCA strategy is characterized by a worse inter-individual uncertainty, offering lower possibility of generalization with respect to the adoption of a ML classifier with an inter-invidivual validation strategy such as LOSO CV.

V. Conclusion

In this work, the adoption of an innovative ML technique to enhance the performance of wearable, SSVEP-based BCIs is proposed. A dedicated ANN, which relies on the adoption of Variable Activation Functions, was designed and implemented to improve the SSVEPs classification, in terms of classification accuracy and time response. First, the proposed algorithm was tested on a benchmark data set based on a traditional SSVEP-BCI setup. Then, the algorithm was tested on a data sets realized by employing highly wearable BCI equipment. In particular, single-channel acquisitions were performed. Most importantly, a pair of AR smart glasses was used instead of traditional, bulky LCDs, in order to guarantee greater wearability, immersivity, and engagement in the fruition of the BCI application. The obtained experimental results showed a significant enhancement of the performance with respect to the traditional state-of-the-art algorithms. In fact, it was demonstrated that such ML classifier can outperform the other processing strategies such as Canonical Correlation Analysis, without increases in computational effort. This represents a starting point towards the development of more 'ready-to-use' BCIs.

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