A ML-based Approach to Enhance Metrological Performance of Wearable Brain-Computer Interfaces

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***Abstract*—In this paper, the adoption of Machine Learning (ML) classifiers is addressed to improve the performance of highly wearable, single-channel instrumentation for Brain-Computer Interfaces (BCIs). The proposed BCI is based on the classification of Steady-State Visually Evoked Potentials (SSVEPs). In this setup, Augmented Reality Smart Glasses are used to generate and display the flickering stimuli for the SSVEP elicitation. An experimental campaign was conducted on 20 adult volunteers. Successively, a Leave-One-Subject-Out Cross Validation was performed to validate the proposed algorithm. The obtained experimental results demonstrate that suitable ML-based processing strategies outperform the state-of-the-art techniques in terms of classification accuracy. Furthermore, it was also shown that the adoption of an inter-subjective model successfully led to a decrease in the 3-σ uncertainty: this can facilitate future developments of ready-to-use systems.**

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

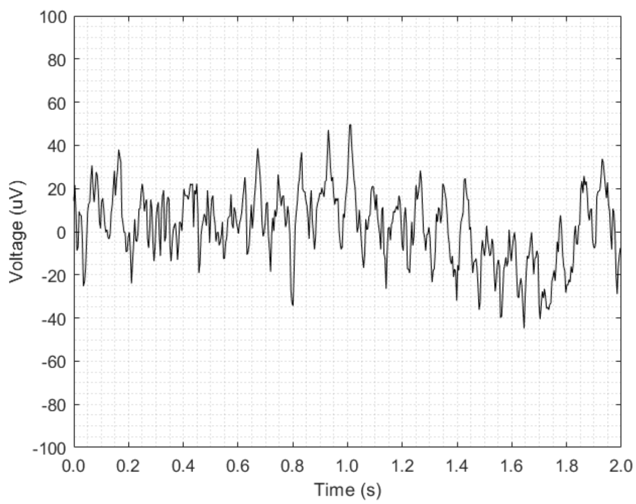
I. Introduction

Brain-Computer Interfaces (BCIs) are a promising technology able to create a direct communication path between human brain and external devices, without using peripheral nerves and muscles [1]. Among the existing BCI paradigms, Steady-State Visually Evoked Potential (SSVEP) has been increasingly adopted in a very wide variety of application fields, such as gaming [2], entertainment [3], industrial inspection [4], and healthcare [5]–[7]. SSVEPs are characterized by a specific brain response to continuously observed flickering stimuli [8], usually in the range from 6 Hz to 30 Hz, although the best Signal to Noise Ratio is achieved in the range from 8 Hz to 15 Hz [9]. Generally, SSVEPs show a sinusoidal-like waveform, with a fundamental frequency equal to that of the gazed stimulus, and often higher harmonics [10], as shown in Fig. 1. Therefore, in pratical applications, such SSVEP-based systems allow the user to send commands to external devices by simply staring at a desired flickering stimulus.

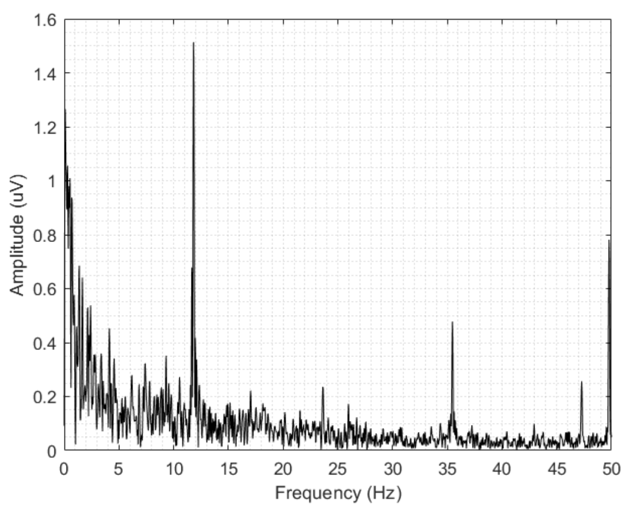
Traditionally, these flickering stimuli are visualized on LCD monitors. Moreover, the elicited SSVEPs are acquired through multi-channel electroencephalogram (EEG) data acquisition [11]. This instrumentation is bulky and inevitably limits the system portability, confining BCI-SSVEP applications to laboratory environments only.

For this reason, more wearable solutions, based on single-channel EEG acquisition, have gained momentum in recent years [12], [13]. Most importantly, the use of Augmented Reality (AR) smart glasses has emerged as a promising strategy to render the flickering stimuli, while ensuring more immersivity and engagement in the fruition of BCI applications [14]–[17].

However, the performance of AR-based BCI are strictly dependent on the specification of the chosen AR device [5], [18]. One of the major characteristics to be addressed is that AR devices are characterized by the non-predictability of the frame rate. This uncertainty inevitably leads to a shift in



(a)



(b)

Fig. 1. Typical SSVEP in time domain (a) and frequency domain (b).

the frequency values of the rendered stimuli, reducing the classification capability of the SSVEP elicited on the users EEG [5].

Therefore, the current challenge is to keep the results obtained by AR-based, single-channel BCI as close as possible to those achieved by traditional setups [19]. To this aim, the adoption of Machine Learning (ML) algorithms represents a promising strategy [20]. In fact, several works have already addressed the use of ML classifiers, such as Support Vector Machine (SVM), k-Nearest Neighbors (k-NN) [21], [22], and Artificial Neural Networks (ANNs) [23], by improving the SSVEPs classification performance.

In this work, the metrological performance of highly-wearable, AR-based SSVEP BCIs are enhanced by adopting the aforementioned ML-based classifiers (SVM, k-NN, ANN). An innovative algorithm was designed, implemented and compared to previously adopted techniques such as traditional Power Spectral Density and Canonical Correlation Analysis.

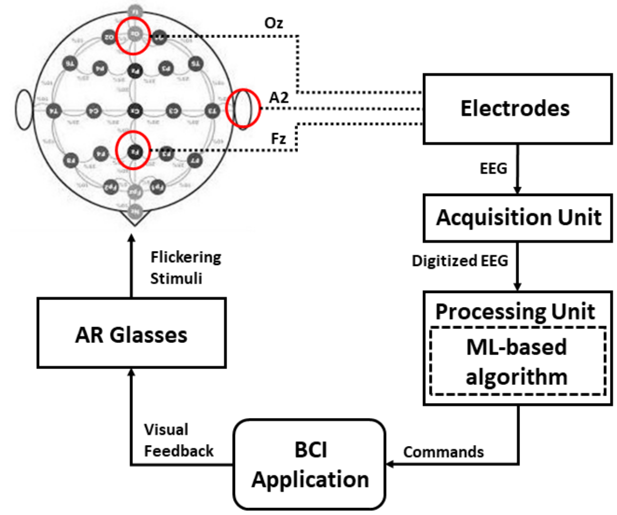


Fig. 2. System Architecture.

The paper is organized as follows. Section II provides a description of the proposed wearable BCI instrumentation, along with the design of the ML-based SSVEP classification algorithm. Then, the experimental metrological characterization is reported and discussed in Section III, along with the obtained results. Finally, in Section IV, conclusions are drawn.

II. Materials and Methods

This work proposes an improvement in the real-time classification of SSVEPs for highly wearable BCI instrumentation. For this reason, the architecture of the single-channel BCI developed in [4]–[6], [24] was considered. Such instrumentation is particularly challenging for wearable applications, since (i) the number of electrodes is very limited, and (ii) AR smart glasses are used to elicit users SSVEPs.

A. Architecture

In Fig. 2, the main block of the system architecture are summarized. *AR Glasses* are used to render two flickering stimuli (at 10 and 12 Hz) for the SSVEPs elicitation. Then, a pair of active and dry *Electrodes* are used to capture the user EEG signal in *Oz* and *Fz* positions according to the 10-20 International System [6]. A third, passive electrode (*Driven Right Leg*, *DRL*) is placed on the earlobe and acts as a reference. The brain signal is collected by a portable *Acquisition Unit*, which sends the EEG Samples to a portable *Processing Unit* in real time. The digitized signal is processed by adopting an enhanced, *ML-based Algorithm*, and the detected command is sent in real time to the *BCI Application*, which actuates the received command providing a visual feedback to the User to show the output of the desired selection.

B. Hardware

The adopted hardware is shown in Fig. 3.

(a) (b) (c)

Fig. 3. Hardware used: a) Epson Moverio BT-200; b) Olimex EEG-SMT; c) Raspberry Pi 4.

- The AR Glasses used in this work are the Epson Moverio BT-200. These Glasses are equipped with Android OS and have a 60 Hz Refresh Rate, with a 23° diagonal field of view.
- The wearable Acquisition Unit chosen to acquire the users brain signals is the Olimex EEG-SMT, a 10-bit, 256 S/s, open source Analog-to-Digital converter.
- The adopted Processing Unit is the Raspberry Pi 4, a single-board PC. A script written in Python 3 receives via USB the digitized signal from the Olimex, process it by means of the Scikit-learn tool, and sends the related output command over TCP/IP protocol to the BCI Application.

C. SSVEP Classification

The proposed SSVEP classification algorithm was designed and implemented by the Authors. The main blocks are shown in Fig. 4. The *EEG Samples* are processed both in frequency and time domains, in order to obtain a reduced number of significant features.

- In the frequency domain, first, a fast Fourier transform (FFT) is performed. Then, the actual SSVEPs *Peaks* are detected around the two rendered stimulus frequencies. In this way, the peaks detection mitigates the uncertainty introduced by the AR Glasses during the generation of the flickering stimuli, resulting in more accurate Power Spectral Densities (PSDs) P_1 and P_2 around the two detected peaks.
- In the time domain, first, a *Band pass Filtering* between 5 and 25 Hz is applied by means of a Finite Impulsive Response (FIR) filter with linear phase response. Then, the Canonical Correlation Analysis (CCA) between the filtered signal and a set of sinewaves, having the frequencies of the two detected peaks and variable phase, is performed. In this way, also the two canonical correlation coefficients ρ_1 and ρ_2 obtained for each frequency are more accurate.

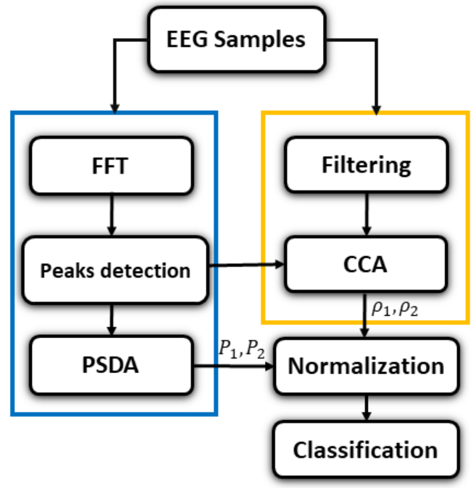


Fig. 4. SSVEP Classification Algorithm with processing in frequency (blue box) and time (yellow box) domain.

Ultimately, for a given brain signal composed of $f_s \cdot N$ EEG samples and two stimulus frequencies to classify (where f_s is the sampling frequency, and N is the number of seconds) only four features are extracted and *Normalized*.

The *Classification* is carried out by means of three ML classifiers: in particular, Support Vector Machine (SVM), k-Nearest Neighbour (k-NN), and Artificial Neural Network (ANN) are employed.

- SVM is a classifier which separates data through a decision hyperplane. SVM maps the inputs in a vector space, finding an optimal hyperplane to maximize the distance from the class boundaries.
- k-NN can be described as follows: given labeled points, a positive integer value k, and a distance measure d for a new input point p, k-NN labels p as the most present class among its k neighbors (through the measure d) that are in the labeled set.
- ANN is a Feed-Forward Artificial Neural Network with one or more layers of hidden neurons between the input and output layers. Each layer has weighted connections (W) entering from the previous layer and outgoing in the next one. In the learning phase, a error function $E(W)$ is minimized through a proper learning algorithm as Gradient Descent.

The proposed algorithm was metrologically characterized by conducting an experimental campaign on 20 untrained and healthy volunteers, by acquiring 24 signals per subject. The chosen flickering frequencies were 10 Hz (rendered on the right side of the screen) and 12 Hz (rendered on the left). Each subject was asked to focus on one stimulus at time, for 10 s. 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 I
CLASSIFIERS, OPTIMIZED HYPERPARAMETERS, AND VARIATION RANGES

Classifier	Hyperparameter	Range
k-Nearest Neighbour (k-NN)	Distance	{Minkowski, Chebychev, Manhattan, Cosine, Euclidean}
	Distance Weight	{equal, inverse, squaredinverse}
	Num Neighbors	{3, 5, 6, 7}
Support Vector Machine (SVM)	C Regularization	{0.01, 0.10, 1.00, 1.77, 5.00, 10.00, 15.00}
	Kernel Function	{linear, radial basis, polynomial}
	Polynomial Order	{2, 3, 4}
Artificial Neural Network (ANN)	Activation Function	{relu, tanh}
	Hidden Layer nr. of Neurons	[5, 505] step: 50
	Learning Rate	{0.0005, 0.0001, 0.0010, 0.0050, 0.0100}
	Validation Fraction	{0.2, 0.3}

The SSVEP algorithm was tested on this realized data set by means of Leave One Subject Out Cross Validation (LOSO CV). It is very promising variant of the k-fold cross-validation approach, as it highlights the inter-individual reproducibility. This procedure divides the data set in 20 folds, where each fold is constituted by a subject. Then, for each combination of the models hyperparameters, the process will run 20 times, each time with a different subject in the test set, taking the remaining ones in the training set. Table I shows the adopted grid search for the tuning of the hyperparameters.

TABLE II
ACCURACY RESULTS AS A FUNCTION OF ML MODELS AND TIME RESPONSE

T (s)	k-NN (%)	SVM (%)	ANN (%)
0.5	72.8 ± 6.2	74.8 ± 6.4	**75.0 ± 6.4**
1.0	80.7 ± 6.6	82.0 ± 6.6	**82.1 ± 6.6**
2.0	88.3 ± 3.9	**89.2 ± 3.5**	**89.2 ± 3.5**
3.0	93.3 ± 3.9	93.6 ± 3.5	**93.7 ± 3.7**
5.0	96.4 ± 3.2	96.4 ± 3.1	**96.7 ± 2.6**
10.0	99.0 ± 1.9	99.2 ± 1.9	**99.4 ± 1.8**

TABLE III
ANN RESULTS COMPARED WITH THE RESULTS FROM THE CCA AND PSD ALGORITHMS

T (s)	CCA [6] (%)	PSD [4] (%)	ANN (%)
0.5	70.8 ± 6.7	-	**75.0 ± 6.4**
1.0	74.8 ± 12.1	-	**82.1 ± 6.6**
2.0	84.9 ± 8.1	81.1 ± 11.4	**89.2 ± 3.5**
3.0	91.0 ± 6.3	87.7 ± 7.8	**93.7 ± 3.7**
5.0	95.4 ± 3.7	96.0 ± 3.9	**96.7 ± 2.6**
10.0	-	98.9 ± 1.5	**99.4 ± 1.8**

III. EXPERIMENTAL RESULTS

Table II summarizes the classification accuracy obtained by the proposed algorithm in function of the acquisition time T and the ML model. The uncertainty is evaluated at 3-σ. As visible, even with 0.5-s time duration, it is possible to evidently discriminate the two classes. Clearly, increasing the duration of T leads to an easier patterns separation and, thus, to an increase of the classification accuracy. Overall, the best performance are obtained by ANN; however, even a more simple classifier like k-NN reaches comparable accuracy levels.

In Table III, a comparison between the results achieved by ANN is compared with those obtained by two classification algorithm previously developed. It can be seen that the the proposed ML-based algorithm provides a significant enhancement. The main contribution to this improvement is given by the peak detection block, which allows to obtain more accurate features both in time and frequency domains, thus mitigating the uncertainty caused by unpredictable frame rate variation of AR devices. In fact, the frame rate of Epson Moverio BT-200 was assessed around the interval [58.0-62.0] Hz. This leads to a generation of the flickering stimuli in the intervals [9.7-10.3], and [11.6-12.4] Hz, instead of the nominal 10 Hz and 12 Hz, respectively. Thus, an adaptive strategy to find the FFT peak position represents the best solution to improve the SSVEP classification, especially in AR-based setup. Finally, it should be noted that both the CCA and PSD strategy are characterized by a worse inter-individual 3-σ uncertainty. Hence, the model proposed in this work offers a greater possibility to be generalized to every users.

IV. CONCLUSIONS

This work addresses a performance enhancement of a highly wearable, single-channel instrumentation for BCI. This BCI is based on the detection and classification of SSVEPs elicited by means of AR smart glasses. The adoption of AR guarantees greater immersivity and engagement with respect to traditional LCD displays. A ML-based algorithm was implemented to improve the SSVEP classification, in terms of classification accuracy and time response. Experimental results on 20 volunteers showed a significant increase in the performance with respect to the consolidated CCA and PSD-based algorithms. In particular, the combined use of time-domain and frequency-domain features leads to a mitigatation of the uncertainty introduced by unpredictable frame rate variation during the rendering of the flickering stimuli. This translates into a better discrimination between classes, that leads to an improvement of the system performance, without a significant increase of computational complexity. In fact, even a simple classifier like k-NN manages to outperform the previously obtained results. This constitutes an advantage in the development of wearable devices, when few channels are used and a small computational complexity is required. Finally, an additional advantage in using ML is the decrease in 3-σ uncertainty. Therefore, such approach can facilitate future developments of ready-to-use systems.

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