Highly wearable SSVEP-based BCI: Performance comparison of augmented reality solutions for the flickering stimuli rendering

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ABSTRACT

A highly-wearable single-channel Brain- Computer Interface (BCI) based on Steady-State Visually Evoked Potentials (SSVEPs) and Augmented Really (AR) is proposed. The SSVEP elicitation is provided by three AR head-mounted displays (HMD), namely Epson Moverio BT-350, Oculus Rift S, and Microsoft HoloLens. Four flickering stimuli, ranging from 8 Hz to 15 Hz, are used. The goal of the work is to carry out a performance comparison of the three aforementioned devices, in terms of stimuli visualization and SSVEPs detection. To this aim, classification accuracy and time response were assessed involving nine healthy volunteers during the experimental activity. The obtained results demonstrate that choosing an adequate HMD to render the flickering stimuli is decisive for obtaining adequate performances.

1. Basic information

Brain-Computer Interfaces (BCIs) are systems aimed at converting the central nervous system (CNS) activity into information, enabling communication between the human brain and artificial devices without the use of muscles or peripheral nerves.

Among all the non-invasive methods used to capture brain signals, electroencephalography (EEG) is certainly the most used [1]. Originally, BCIs based on EEG were applied mostly for rehabilitation purposes, providing a way to assist people with motor disabilities [2]. More recently, the application of BCI has been extended also to non-medical fields, such as gaming [3], industrial inspection [4], fatigue detection [5], etc.

Different paradigms can be used for implementing EEG-based BCIs, depending on the task to be performed by the user and on the brain signal to be decoded. Among these paradigms, Steady-State Visually Evoked Potentials (SSVEPs) represent an interesting solution in terms of Signal-to-Noise Ratio (SNR), Information Transfer Rate (ITR), reproducibility and robustness to artifacts [6]. SSVEPs are exogenous potentials that are induced in the primary visual cortex when the user is observing a flickering stimulus [7]. Generally, the detected SSVEP exhibits a fundamental frequency (at the same value of the targeted frequency stimulus) and often higher harmonics. In SSVEP-based BCI, the system allows the user to perform a selection by simply staring at the related flickering stimulus, as implemented in [6], where the movement of an humanoid robot was driven by the user by staring at two arrows flickering at different frequencies, associated to Move to left and Move to right commands. In traditional applications, the visual stimuli are commonly generated through light-emitting diodes (LEDs) [8], or liquid crystal display (LCD) monitor [9]. However, these solutions place limits on the mobility and portability of the system.

On the other hand, augmented reality head-mounted displays (AR-HMDs) offer a solution to guarantee flexibility and wearability [10]. In this case, the flickering stimuli are superimposed to the surrounding environment, allowing the user to interact more easily with the real world.

Another goal to pursue in wearable systems is to effectively decrease the number of necessary electrodes (typically eight in traditional EEGs [10]), aiming to improve the use of BCIs in everyday life, still preserving acceptable performance. Single-channel BCIs (with only two electrodes for the differential input and one electrode for the reference), represent a highly-wearable alternative to traditional multi-channel BCIs, strongly reducing complexity and user discomfort without performance degradation [6,11–14].

On the basis of these considerations, in this work, the authors propose a highly-wearable single-channel SSVEP-based BCI, by using AR to generate four concurrent flickering stimuli. The main objective is to evaluate the user experience, in terms of both stimuli visualization and SSVEPs detection, considering three different AR device: Epson Moverio BT-350, Oculus Rift S, and Microsoft HoloLens.

The paper is organized as follows. Section 2 describes the system architecture, focusing on the chosen AR devices, on the acquisition unit and, finally, on the proposed SSVEP detection algorithm. In Section 3, the obtained experimental results are presented. Finally, in Section 4 conclusions are drawn.

2. Description of the AR-BCI system

In this section, the design of the proposed highly wearable single-channel SSVEP-based BCI is presented. In particular, the description of the system architecture, along with the devices used and the proposed detection algorithm, is provided.

2.1. Architecture

The system architecture is shown in Fig. 1. The AR Display, worn by

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the user, renders the visual stimuli to elicit SSVEP activity. Three EEG electrodes are used for a single-channel differential acquisition: two active electrodes are placed on the user's scalp in *Oz* (Occipital Midline) and *Fz* (Frontal Midline) positions, according to the international 10–20 System [4], and connected to the positive and negative input of the acquisition unit. Furthermore, a passive electrode (*Driven Right Leg*, DRL) is placed on the earlobe (*A2*) to reduce common mode interference. The captured brain signal is then digitized and processed by a portable acquisition unit and by a processing unit, respectively. Then, the related output command is available, and it can be sent to activate/control the chosen target device (clearly, the target device to be controlled depends on the purpose of the application [6,11]). Finally, the target device gives a visual feedback to the user, as a result of the user's selection.

- AR Display: The three selected AR devices are shown in Fig. 2 and described as follows.
  a) Epson Moverio BT-350: is a set of AR smart glasses, with a diagonal field of view of 23°, and a nominal refresh rate of 30 Hz. The AR environment, realized in Android Studio, renders four white squares, placed at the four edges of the screen. The flickering frequencies chosen were 8 Hz, 10 Hz, 12 Hz and 15 Hz.
  b) Oculus Rift S: is a Virtual Reality (VR) based HMD, integrated with a HD stereo camera (Zed Mini to obtain an AR video see-through (VST) environment. The Oculus refresh rate is 80 Hz, and the AR environment was made with Unity and renders four white location-based flickering squares. The location-based rendering manages to reduce interferences during the SSVEP elicitation when the user tries to look at the desired stimulus. In this case, in fact, the flickering icons are not anchored to the AR screen, but are linked to a particular position in the real world. The chosen frequency values were sub-multiples of the nominal refresh rate: 8.00 Hz, 10.00 Hz, 11.43 Hz and 13.33 Hz.
  c) Microsoft HoloLens: is a more expensive AR optical see-through (OST) HMD, with a diagonal field of view of 34°, and a nominal refresh rate of 60 Hz. Similarly to Oculus Rift, the AR environment was realized in Unity and shows four white location-based squares. The four frequency values chosen were 8.57 Hz, 10.00 Hz, 12.00 Hz, and 15.00 Hz, submultiples of the nominal refresh rate.
- *EEG Acquisition Unit*: The Olimex EEG- SMT (Fig. 3(a)), a 10-bit, 256 S/s, differential input Analog-Digital Converter (ADC), was used to digitize the brain signals acquired through the three electrodes.

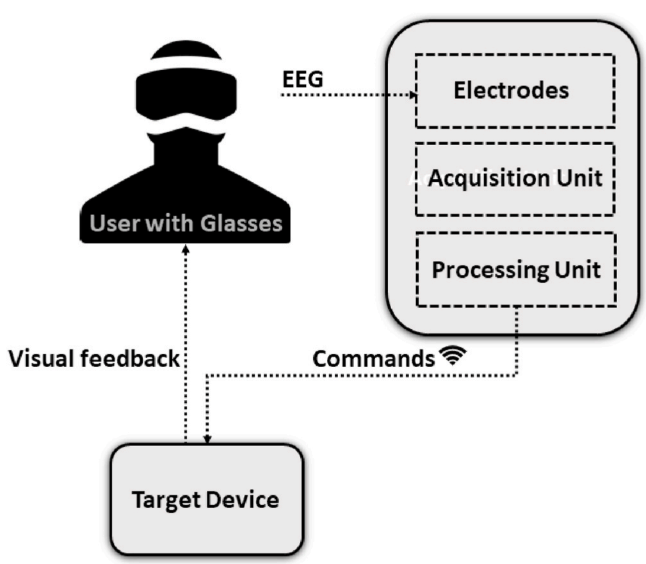

Fig. 1. BCI-AR SSVEP architecture.

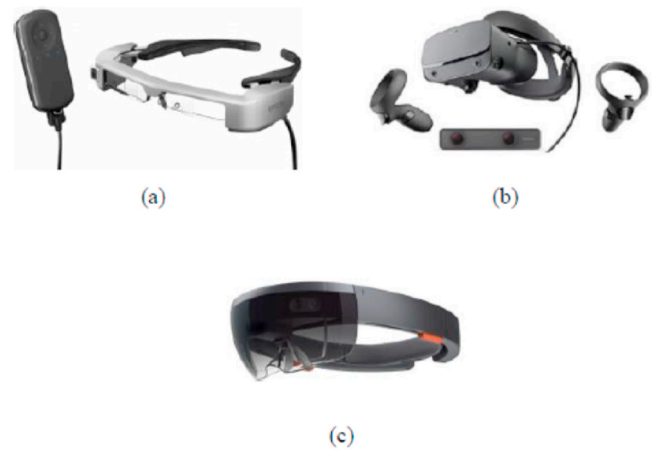

Fig. 2. AR HMD: a) Epson Moverio BT-350; b) Oculus Rift S with Zed mini; c) Microsoft Hololens.

- *EEG Processing Unit*: The EEG Processing Unit chosen is the Raspberry Pi 4 (Fig. 3(b)), a portable single-board computer connected to the acquisition unit via USB. After the SSVEP detection, the Raspberry sends over TCP/IP the related command to the specific target of the application, as successfully conducted in Refs. [6,11].

2.2. SSVEP detection algorithm

The proposed SSVEP detection algorithm carries out a Pearson correlation coefficient analysis in time domain [6].

The brain signal is acquired by a time window of length T and filtered with a band-pass finite impulse response (FIR) filter between 5 Hz and 25 Hz. The filtered signal is then correlated with a set of sine waveforms Φ_i having the same frequencies of the generated flickering stimuli. Therefore, the Pearson correlation coefficients [6,11] ρ_i are obtained for all the generated frequencies.

Consequently, if the maximum value among the correlation coefficients is greater than the second largest one of a certain threshold, a signal fragment is marked as recognized. Otherwise, a new signal fragment of duration T is processed, considering an overlap of T/2 with the previous one.

3. Experimental results

The goal of the experimental activity was to evaluate the user experience, in terms of stimuli visualization and SSVEP detection, for the three AR HMDs involved. Nine volunteers were asked to wear the AR-BCI equipment and stare at one stimulus at time for 10 s. For each HMD, 20 brain signals per subject were acquired. Classification Accuracy (defined as the percentage of brain signal correctly marked) and Time Response (defined as the average time needed to the system to classify a brain signal), were measured to evaluate the SSVEP detection performances for each HMD.

In Fig. 4 the obtained results for the three considered HMD are shown. It can be noticed that the best performances are obtained when using the Microsoft Hololens. However, for time response values ranging from 2.0 s to 2.5 s, Oculus Rift S reaches comparable classification accuracy values: this good performance is the result of using a location-based AR rendering of the flickering icons. In the case of Epson Moverio, instead, the four flickering icons are always anchored to the edges of the screen: this inevitably leads to undesired inter-stimuli interferences while the user tries to look at the chosen flickering stimulus, thus decreasing the classification accuracy. In the range 2.8–4.0 s, the performance of the Oculus Rift S was slightly worse than HoloLens': during the trials, in fact, some users felt motion sickness effects induced by the VST technology and the device ergonomics.

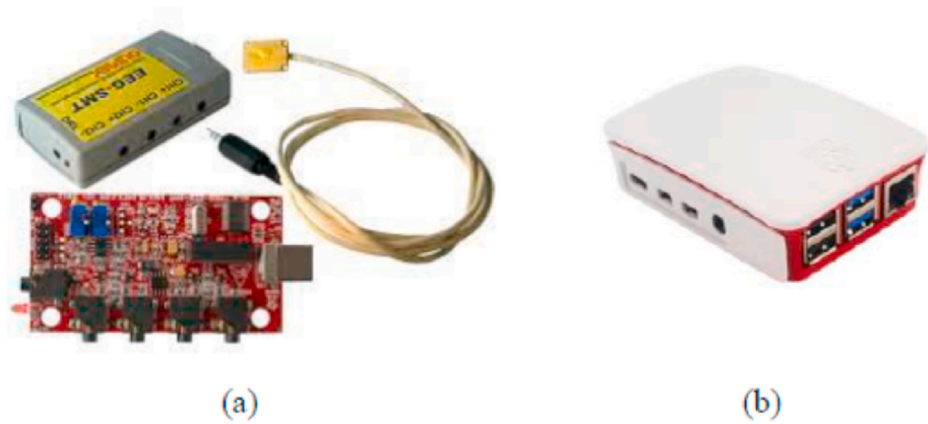

Fig. 3. BCI Equipment: a) Olimex EEG-SMT; b) Raspberry Pi4.

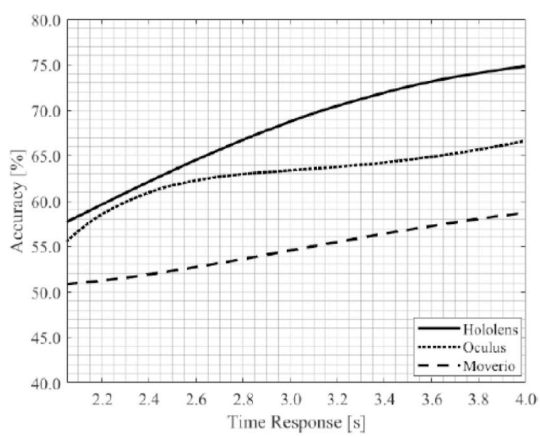

Fig. 4. Accuracy vs Time Response for the three AR devices.

4. Conclusions

This work proposes a highly wearable SSVEP-based single channel BCI, where three different AR HMDs, namely Epson Moverio BT-350, Oculus Rift S (integrated with Zed Mini), and Microsoft HoloLens, were chosen to generate four concurrent flickering stimuli. The main challenge, regarding the performance comparisons between the aforementioned AR devices, was explored. Experimental results demonstrate that choosing an adequate HMD to render the flickering stimuli is crucial for obtaining acceptable performances: the overall user experience, in fact, is strongly dependent on how the flickering stimuli are rendered. With Microsoft HoloLens and Oculus Rift S whose rendering is location-based, the classification accuracy resulted almost 20% larger than the values obtained with Epson Moverio BT-350. On the other hand, some user felt motion sickness effects during the trials with Oculus Rift S, due to the VST technology of the HMD. Considering the large difference of cost between Microsoft HoloLens and the other two selected devices, further work will be carried out to identify the HMDs that could provide an optimal trade-off of cost, ergonomics, and rendering capability, aiming to achieve fully wearable, practical, and affordable systems for daily life, wearable applications [15] in the 4.0 Era context [16].

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