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Assessment of high-frequency steady-state visual evoked potentials from below-the-hairline areas for a brain-computer interface based on Depth-of-Field

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ABSTRACT

Background and Objective: Recently, a promising Brain-Computer Interface based on Steady-State Visual Evoked Potential (SSVEP-BCI) was proposed, which composed of two stimuli presented together in the center of the subject's field of view, but at different depth planes (Depth-of-Field setup). Thus, users were easily able to select one of them by shifting their eye focus. However, in that work, EEG signals were collected through electrodes placed on occipital and parietal regions (hair-covered areas), which demanded a long preparation time. Also, that work used low-frequency stimuli, which can produce visual fatigue and increase the risk of photosensitive epileptic seizures. In order to improve the practicality and visual comfort, this work proposes a BCI based on Depth-of-Field using the high-frequency SSVEP response measured from below-the-hairline areas (behind-the-ears).

Methods: Two high-frequency stimuli (31 Hz and 32 Hz) were used in a Depth-of-Field setup to study the SSVEP response from behind-the-ears (TP9 and TP10). Multivariate Spectral F-test (MSFT) method was used to verify the elicited response. Afterwards, a BCI was proposed to command a mobile robot in a virtual reality environment. The commands were recognized through Temporally Local Multivariate Synchronization Index (TMSI) method.

Results: The data analysis reveal that the focused stimuli elicit distinguishable SSVEP response when measured from hairless areas, in spite of the fact that the non-focused stimulus is also present in the field of view. Also, our BCI shows a satisfactory result, reaching average accuracy of 91.6% and Information Transfer Rate (ITR) of 5.3 bits/min.

Conclusion: These findings contribute to the development of more safe and practical BCI.

1. Introduction

Biological signals are a key factor in development of non-conventional channels of communication between humans and machines. Brain-Computer Interfaces (BCIs) play an important role as they allow to extract information from brain signals and relating them with commands into an application [1,2]. For instance, people with no muscular and speech ability can use BCIs to create interaction links with assistive and rehabilitation technologies that can improve their quality of life [3,4].

One of the most common BCI paradigms is based on Steady-State Visual Evoked Potential (SSVEP), which is a brain response from visual cortex elicited by a periodic visual stimulation [5,6]. In Electroencephalogram (EEG), this potential represents oscillatory components with the same stimulus frequency (and/or its harmonics) [7]. This response can be divided into three bands: low- (up to 12 Hz), medium- (12–30 Hz) and high-frequency ($\geq$ 30 Hz) [7]. Low-frequency range has higher amplitudes, which implies an easier detection [8], however, its disadvantage is the fast visual fatigue generated [9].

In SSVEP-BCIs, each command can be represented by a visual stimulus at a specific frequency [10,11]. Thus, conventional SSVEP-BCIs users are able to send commands to the computer by redirecting their gazing to the target stimulus location (Fig. 1) [2]. However, paralyzed individuals who cannot control their muscular movements will have difficulties using these conventional SSVEP-

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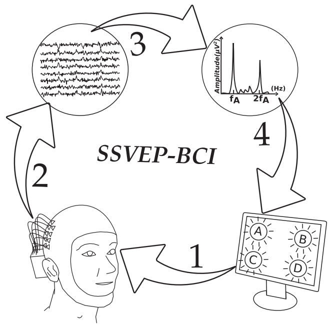

Fig. 1. Diagram of a conventional SSVEP-BCI. (1) Subject needs to conduct eye movements to gaze, for instance, at target *A* flickering at frequency f_A. (2) EEG signals are measured on the occipital area (hair-covered area) from the scalp. (3) These data are processed to extract features, such as peaks at f_A and its harmonics. (4) The features are classified and translated into commands.

BCIs. Thus, in order to reduce the need of voluntary movements, BCIs that present two stimuli close to each other, or superimposed, have been proposed [12–16]. However, stimuli proximity increases the neural competition in the visual cortex [17], resulting in a reduction of classification accuracy [18,19].

With the aim of reducing the visual stimuli competition as well the necessary voluntary movements, Cotrina et. al [20] proposed a SSVEP-BCI composed of two low-frequency stimuli presented together in the center of the subject's field of view, but in different longitudinal distance. Thus, users were able to select one of them by shifting their eye focus [20] (Fig. 2). When human eye focuses on an object, the range of distance for which objects produce the acceptably sharp retinal image is known as Depth-of-Field [21]. Objects positioned out of the Depth-of-Field appear blurred.

In Cotrina et. al [20], the EEG signals were collected through wet electrodes placed on occipital and parietal regions (hair-covered areas). However, in addition to having their hair dirty because the use of gel, even using dry electrodes, people with severe motor disabilities generally need to stay with their heads supported by a headrest, which makes it difficult to use this kind of BCIs in everyday life.

Due to these limitations of practical use, nowadays, researchers are working to transfer the BCIs from the scientific environment to the daily life of the patient, which implies the need of more practical BCIs. For this purpose, measuring the EEG from below-the-hairline areas (behind-the-ears and face) presents advantages to the user, and recently, these kinds of BCIs using stimuli in low and/or medium frequency have been reported in the literature [25–28]. However, as mentioned previously, a known disadvantage of using these frequency ranges is that they can produce visual fatigue, and can also increase the risk of photosensitive epileptic seizures and migraine headaches [7,9,29].

Despite being safe, practical and comfortable for people suffering severe motor disabilities, research about BCIs based on both below-the-hairline areas and high-frequency visual stimuli has been few explored in the literature. The reason is because the amplitude of SSVEPs in high-frequency is quite reduced, making it hard to implement a BCI [30].

Recently we have shown that chromatic and luminance stimuli allow the achievement of higher amplitudes and higher signal-to-noise ratio (SNR) from behind-the-ears areas, even when using high-frequency SSVEP [31]. Our study showed that in the high-frequency range (30–40 Hz), the best response was obtained in green-blue stimulation [31]. Therefore, it is reasonable to believe that high-frequency SSVEPs with EEG electrodes positioned below-the-hairline areas could be used to implement a SSVEP-BCI based on Depth-of-Field. To our best knowledge, high-frequency SSVEPs from hairless areas to develop an online BCI has not yet been used, as the proposed in this work.

Thus, this study aims to answer three main questions: (1) Can high-frequency SSVEP measured from below-the-hairline areas be modulated by shifting eye focus? (2) Can the SSVEP measured from these hairless areas be suitable for BCI usage? (3) What is the system performance for online mode? The article follows with an explanation of the materials and methods used in this evaluation. Lastly, some important aspects of the results are shown and discussed.

2. Materials and methods

2.1. Data acquisition

This research was carried out in compliance with the Helsinki declaration, and the experiments were conducted according to the rules of the Ethics Committee of the Federal University of Espirito Santo (UFES/Brazil), under registration number CAAE: 64797816.7.0000.5542. Four healthy subjects (ages 24.0 ± 4; 3 male; 1 female) participated in this study, which was similar to other works [32–35].

All measurements were noninvasive and the subjects were free to withdraw at any time without any penalty. A clinical EEG signal recording equipment (BrainNet BNT-36) was used. The EEG was

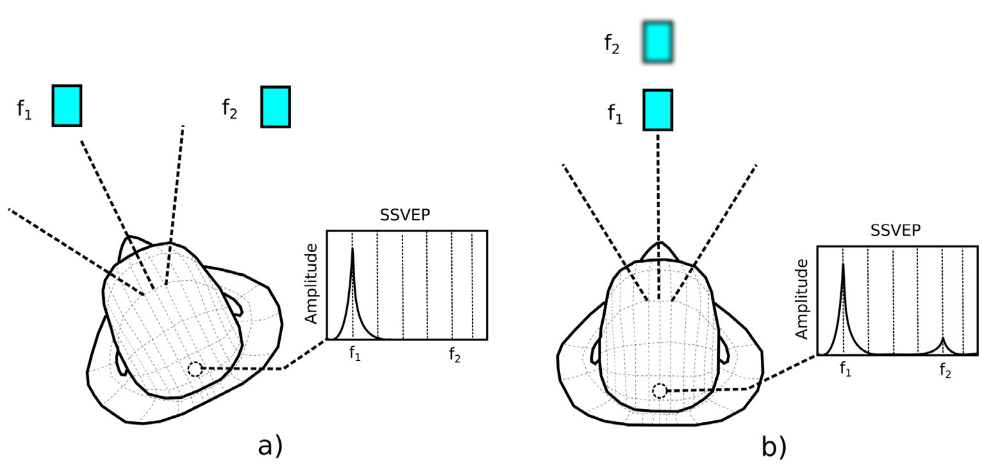

Fig. 2. (a) Illustration of conventional SSVEP-BCI; (b) Alternative SSVEP-BCI stimuli setup based on Depth-of-Field. Users can select one out of two stimuli by the accommodation of the eye, which is the mechanism that adapts the optics properties of the eye in response to focus on a near or far object [22–24].

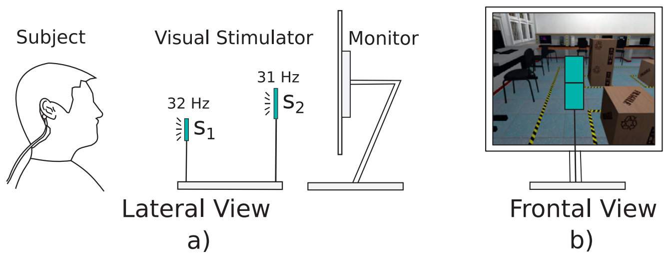

Fig. 3. Layout of the SSVEP-BCI stimulation setup. a) Lateral View; b) Frontal View.

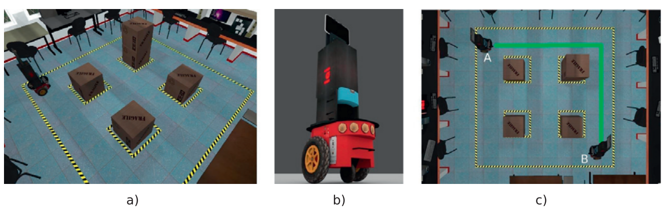

Fig. 4. Experimental environment for evaluation of the proposal BCI. a) VE developed; b) Virtual robot used in the experiments; c)Task used for online evaluation.

preprocessed using a 4th order Butterworth filter with cut-off frequencies set at 25 and 40 Hz. EEG was recorded by electrodes placed on TP9 and TP10 positions (behind-the-ears) of the international 10-10 system, with the reference on the forehead (Fpz) [31]. The sampling frequency was fixed at 200 Hz, and the ground electrode was placed on the left ear.

2.2. Visual stimulation

The stimulation was composed of two frosted RGB LEDs positioned 20 cm apart, each one illuminating a diffusion board (Fig. 3). The stimulation signals were generated through programming the microcontroller ATMega2560/16MHz, which is a part of the Arduino Mega 2560 Development Board. The two stimuli were generated as square waveforms with main frequency at 31 and 32 Hz, and duty-cycle of 50%. For the experiments, we used the stimulation parameters based on our previous study [31], which has used green (525 nm) and blue (465 nm) colors, as this combination elicits SSVEPs with the best SNR in the high-frequency range [31].

2.3. Protocol

The first experiment of our study aimed to analyze whether it is possible to modulate high-frequency SSVEP responses from below-the-hairline areas using a visual stimulation based on Depth-of-Field. The subjects were asked to focus on each stimulus (S_1 and S_2) for 20 s [36], with both stimuli activated. The subjects were seated on a comfortable chair 60 cm away, in front of the stimulation system.

The second experiment was performed with subjects interacting with a mobile robot into a Virtual Environment (VE) [37] using the BCI (Fig. 4). The VE was created in the *Unity Game Engine*, whereas the robot and its movements were built in the open source software *Blender 3D*. Furthermore, the textures were created using a free license software *Gimp*. In this experiment, the subjects performed the route (A–B) shown in Fig. 4, by sending control commands to the virtual robot through our BCI.

The commands implemented in the system were defined as: i) move a meter ahead, which corresponded to the focus on the S_2 stimulus; ii) rotate 30 degrees to the right when the focus was on the S_1 stimulus (Fig. 3). Each robot animation takes 2 seconds.

Then, to complete the task, the following sequence of commands is required: i) four consecutive advance commands (the robot was moved 4 m forward); ii) three consecutive turn right commands (the robot turns 30° on each command); iii) three consecutive advance commands to reach point B; iv) three consecutive turn right commands to complete the task.

Each time a command was detected the EEG acquisition was stopped. When the robot reached the new position and was able to receive a new command, the EEG acquisition resumed. Thus, the BCI is working in a synchronous mode.

2.4. Statistical analysis

To conduct a statistical analysis of the presence of periodic signals, such as SSVEP response onto the EEG [36], the Multivariate Spectral F-test method (MSFT) is used [36]. This method compares the amplitude at the stimulus frequency with respect to the amplitude of background noise at neighboring frequencies, as shown in Eq. (1) [36]:

$$\hat{\phi}_N(f_o) = \frac{\sum_{j=1}^{N} \left|Y_j(f_o)\right|^2}{\sum_{j=1}^{N} \left[\frac{1}{L} \sum_{\substack{i=o-L/2 \\ i\neq o}}^{i=o+L/2} \left|Y_j(f_i)\right|^2 \right]}, \tag{1}$$

where the variable o represents the index of the frequency (31 Hz or 32 Hz) in the values calculated using the FFT of the EEG signal, f_o is the stimulation frequency, N is the number of EEG channels, L is the number of neighboring frequencies (this work used $L = 20$, i.e. $\pm$ 0.5 Hz [36]), $Y_j(f_o)$ and $Y_j(f_i)$ are the Fourier transform of the jth signal evaluated at frequencies f_o and the ith closest neighboring frequency to f_o, respectively. The threshold for hypothesis rejection of the absence of evoked response (H_o) is the critical value [38], given by:

$$\hat{\phi}_{N_{crit}}(f_o) = F_{crit_{2N,2NL,\alpha}} \tag{2}$$

where $F_{crit_{2N,2NL,\alpha}}$ is the critical value of the F-distribution with $2N$ and $2NL$ degrees of freedom for a significance level of $\alpha = 0.01$. Thus, in case of the detector value (Eq. (1)) is above of the threshold value (Eq. (2)), the hypothesis of presence of periodicity is accepted.

2.5. Online analysis

In order to recognize the commands for control of the mobile robot into the virtual environment, the EEG signal is analyzed by a sliding window of 4 s length moved in steps of 0.25 s (i.e., the EEG signal processing is performed four times per second). Then, 5 s of EEG signal are needed to obtain a classification. The Temporally Local Multivariate Synchronization Index (TMSI) method [39] is performed every 0.25 s, using the criterion of maximum value of synchronization index for the SSVEP target recognition (31 Hz and 32 Hz). Then, the final decision to send a correct command is carried out after receiving a same target four times consecutively, otherwise the BCI output is idle, and the acquisition of the signals is resumed. Thus, the BCI does not send a command to the robot and, consequently, the robot stays stopped until a new command is detected. Then, it is needed to acquire 1 more second of EEG.

The BCI performance was evaluated through accuracy and ITR indices. To estimate the accuracy, correct and incorrect commands were considered. An incorrect command did not correspond with the expected movement of the robot, for instance, in the case when the robot must turn to the right and the command to go ahead was detected.

The time used to calculate the ITR was the complete time to send a command, i.e. starting when the subject gazed at the stimulus up to the command was sent to the robot.

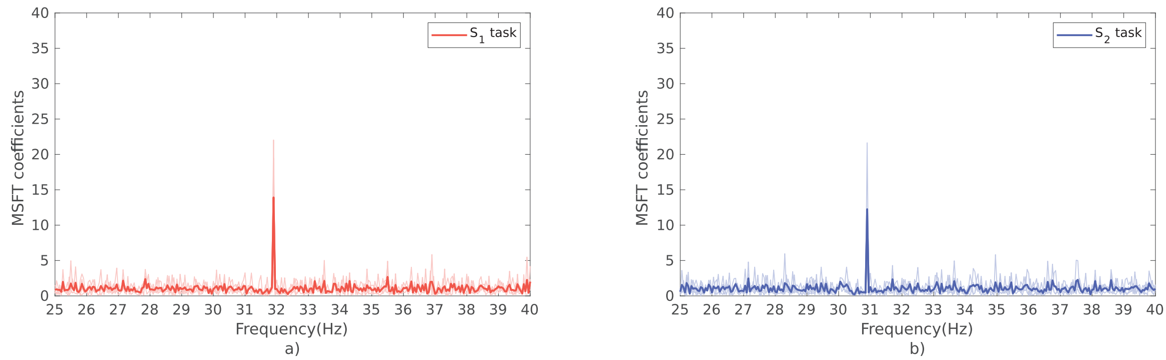

Fig. 5. MSFT coefficients corresponding to the average of trials of all subjects. a) The focus was on S_1 stimulus. b) The focus was on S_2 stimulus.

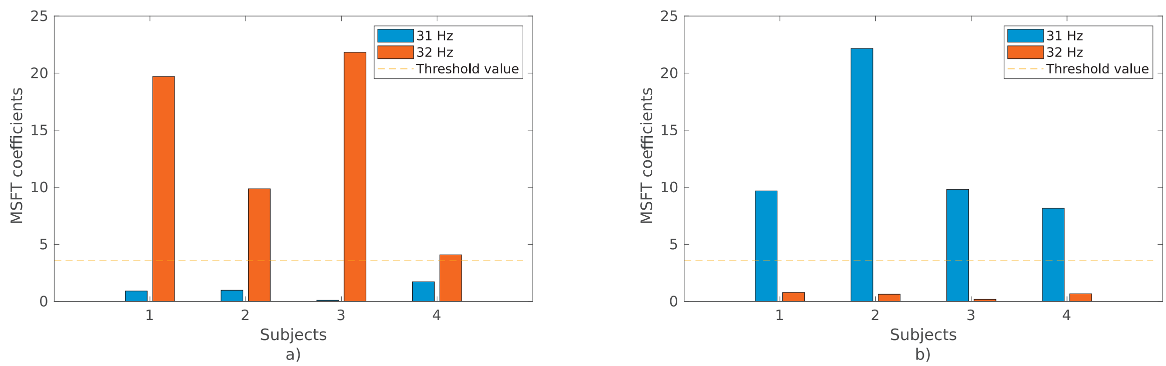

Fig. 6. MSFT coefficients corresponding to frequency of S_1 and S_2 stimuli. a) The focus was on S_1 stimulus. b) The focus was on S_2 stimulus.

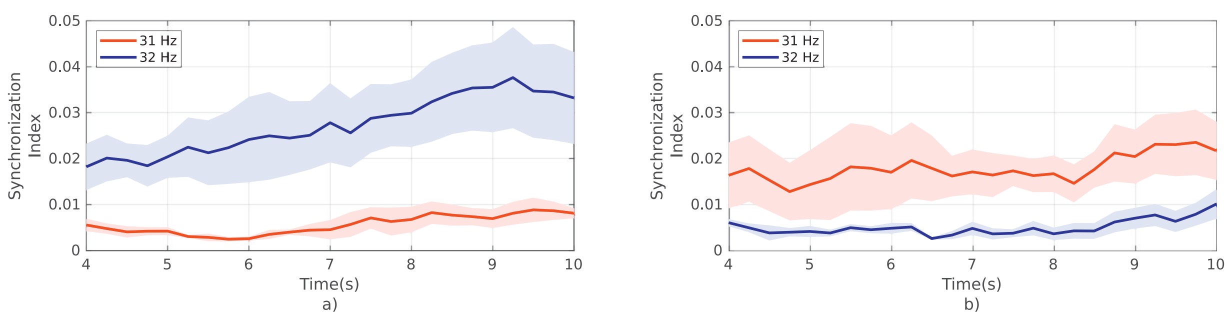

Fig. 7. Synchronization indices of the TMSI method corresponding to the average together with standard error. a) The focus was on S_1 stimulus. b) The focus was on S_2 stimulus.

3. Results and discussion

Fig. 5 shows the MSFT coefficients calculated by Eq. (1) of the SSVEP response elicited by the visual stimuli. The SSVEPs elicited by the visual stimulation setup were consistent and accurate. In both situations (focus on S_1/S_2 stimulus), each response contains the peak in the expected frequency. In both cases, the peak of the other frequency was absent even though both visual stimuli were activated.

Fig. 6 shows the bars representing the value of the MSFT coefficients at frequencies of focused/non-focused stimulus for each subject in the situations: a) focus on S_1; b) focus on S_2. It can be observed that the detector coefficient is above the threshold value resulting in the hypothesis of evoked response presence being accepted. Thus, the focused stimulus elicited distinguishable SSVEP pattern independent of the non-focused stimulus which were also present in the field of view.

Fig. 7 shows synchronization indices calculated with the TMSI method using four-second sliding windows (steps of 0.25 s) for the two situations (focus on S_1/S_2 stimulus). The results reveal that the SSVEP amplitude was modulated according to the eye focusing mechanism. For both cases, it can be noticed throughout the trial that the values of the synchronization indices related to the frequencies of the focused stimuli are higher than the other ones and vice versa.

The results of the online evaluation are shown in Figs. 8 and 9, from which it resulted that the subjects were able to perform the proposed tasks with an average accuracy of 91.6% and ITR of 5.3 bits/min. Notice that, according to [40], accuracy above 70% is considered acceptable to achieve effective communication in a BCI with binary choice. Thus, based on these results, we believe that our proposed BCI is considered suitable to be used in practical cases as, for example, for alternative communication interfaces.

As a discussion about this study, although conventional SSVEP-BCIs are becoming robust systems, they are still not suitable for all patients. For that reason, recently, Cotrina et al. proposed a setup based on the Depth-of-Field, which became a complementary method to the attention-based SSVEP paradigm using low-frequency stimuli (5.6 Hz and 6.4 Hz) and occipital channels [20].

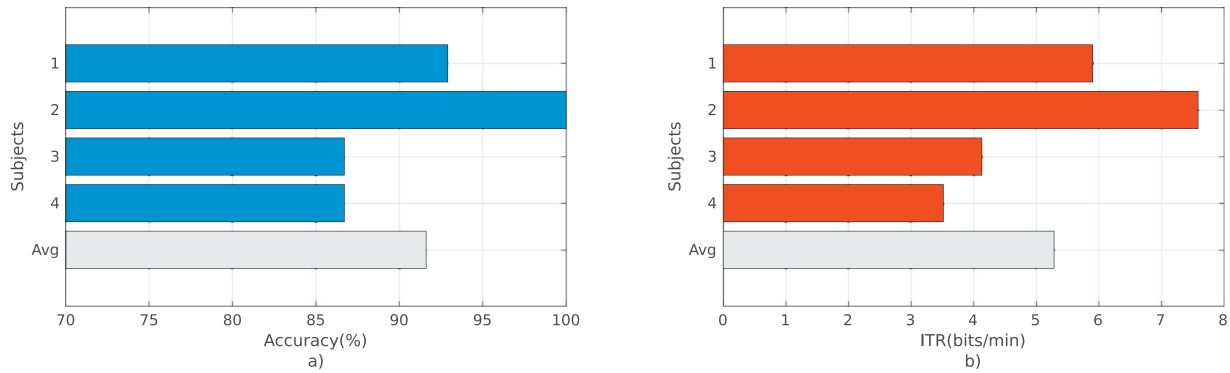

Fig. 8. Accuracy and ITR of the online evaluation.

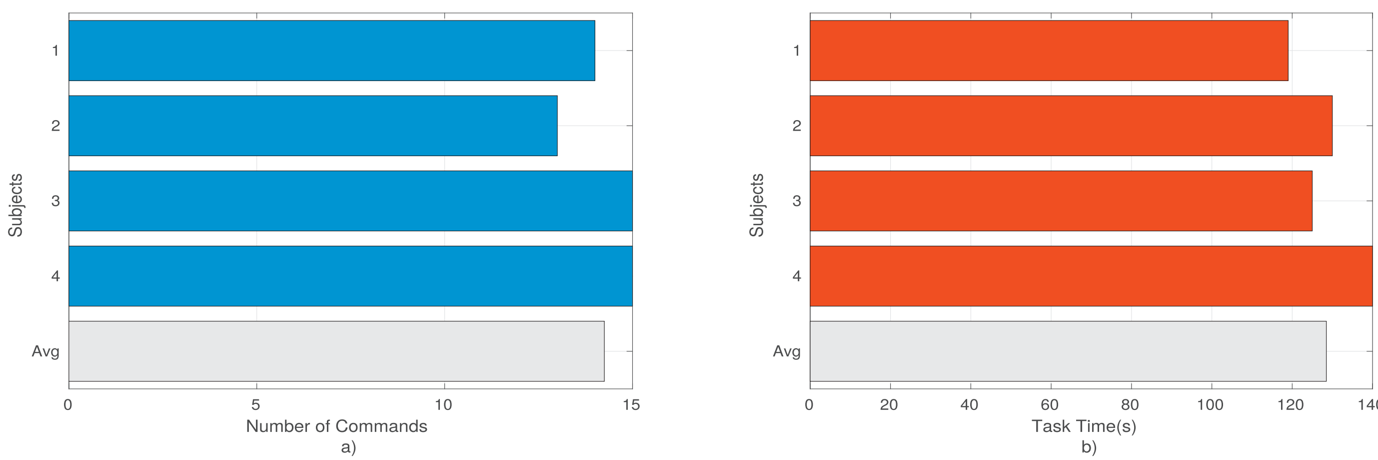

Fig. 9. Results of the online evaluation.

Table 1
Summary of characteristics of related studies.

Study	Accuracy(%)	ITR(bits/min)	Analysis	High-frequency	Hairless area
Cotrina et al. [20]	93	9.58	Offline	No	No
Our work	91.6	5.3	Online	Yes	Yes

Although our accuracy and ITR values were slightly lower than their work, our evaluation reaching satisfactory performance (See Table 1). Furthermore, our BCI uses green-blue chromatic flicker, which is considered the safest stimulus for the human visual photosensitivity [41].

4. Conclusions

In this work, we analyzed high-frequency Steady-State Visual Evoked Potentials (SSVEPs) measured from below-the-hairline areas for a SSVEP-BCI based on Depth-of-Field. Offline results revealed that the proposed visual stimulation setup elicited suitable responses for a practical use. Also, it was observed that the high-frequency SSVEP from hairless regions can be modulated by the eye focusing mechanism. Our BCI was then tested online in a virtual environment where the subjects had to steer a virtual robot. The results showed a satisfactory performance for practical use (accuracy and ITR of 91.6% and 5.3 bits/min, respectively). Additionally, our BCI uses comfortable stimuli (high-frequency range), practical electrodes placement and does not require a calibration phase by users.

Declaration of Competing Interest

The authors declare that they have no conflict of interests.

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Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.cmpb.2019.105271.

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