Wearable Brain-Computer Interface Instrumentation for Robot-Based Rehabilitation by Augmented Reality

Wearable Brain-Computer Interface instrumentation for robot-based rehabilitation by Augmented Reality

Pasquale Arpaia[1], Luigi Duraccio[2], Nicola Moccaldi[1], and Silvia Rossi[1]

***Abstract*—An instrument for remote control of robot by wearable Brain Computer Interface is proposed for rehabilitating children with attention deficit/hyperactivity disorder (ADHD). Augmented Reality (AR) glasses generate flickering stimuli and a single-channel electroencephalographic Brain Computer Interface detect the elicited Steady State Visual Evoked Potentials (SSVEP). This allows to benefit from the SSVEP robustness by leaving available the view of robot movements. Together with the lack of training, a single channel maximizes the device's wearability, fundamental for the acceptance by ADHD children. Effectively controlling the movements of a robot through a new channel enhances rehabilitation engagement and effectiveness. A case study at an accredited rehabilitation center on 10 healthy adult subjects highlighted an average accuracy higher than 83%, with Information Transfer Rate (ITR) up to 39 bits per minute. Preliminary further tests on 4 ADHD patients between 6 and 8 years old provided highly positive feedback on device acceptance and attentional performance.**

I. Introduction

Attention-deficit/hyperactivity disorder (ADHD) is a childhood-onset neuropsychiatric disorder, characterized by persistent and impairing inattention, hyperactivity, and impulsiveness. In 2013, the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition [1], stated a prevalence of 5%. In 2018, more recent studies estimated a significant increase (over 10% only in USA) [2]. Accordingly to European Consensus Statement on diagnosis and treatment of adult ADHD, this is among the most common psychiatric disorders of childhood, often persisting into adulthood and even old age [3].

Existing treatments of children combine different approaches: pharmacological, behavioral, occupational, cognitive, and psychological [4]. Among the behavioral appraoches, Brain computer Interface (BCI) has often been proposed as an innovative method for both detection [5] and treatment of ADHD [6], [7], [8], [9], [10]. In particular, BCI translate electrical brainwaves into information regarding a mental state or a will of the user. In health research for children, BCI is applied for (i) diagnostics, (ii) communication, (iii) robotic control (e.g., artificial limbs), and (iv) neurorehabilitation. The proposals depend on the measured brainwaves: (i) P300; (ii) steady-state visual evoked potentials (SSVEPs); (iii) event-related potentials (ERPs); and (iv) sensorimotor rhythms (SMR). SSVEPs and ERPs are potentials triggered by an event. SSVEPs are exogenous potentials [11] because the response, measured after less than 100 ms, is physiological. ERPs have higher latency and involving higher mental processes; for this reason they too are defined as endogenous [12]: they are triggered by the mental act of the subject who realizes the stimulus. Moreover, P 300: is an ERP potential occurring 300 ms after a stimulus, largely used in BCI speller application [13]. Sensorimotor rhythm refers to a variation of power in the band 8-25, over sensorimotor cortex. This variation is generated by the execution or the imagination of a movement of a part of the body [14]. The SSVEPs, with respect to the other signals, have a fixed frequency oscillation that allows an easier detection, even using less electrodes and in conditions of greater noise. Historically, the use of BCI in ADHD treatment borrows from the utilization of neurofeedback in training aimed at reducing seizures in epilepsy [15]. The goal of neurofeedback is to train the individual to normalize abnormal neural frequencies by increasing awareness of a normalized EEG pattern. A new approach always based on biofeedback seeks to make the exercise more engaging for children by a game of increasing difficulty [16]. The game progresses at a speed proportional to child's attention level . Another study proves that the playful aspect determining the higher involvement is directly linked to the attentional performance [17]. Some further works verified the increase in effectiveness of the same rehabilitative activity when a robot was involved [18]. According to [19], the robot can not only be considered a useful educational tool, but also a sort of body extension. This allows to experiment and live real "augmented experiences", able to work both on the perceptive-emotional and on the cognitive level. In the case of children under the age of eight, further challenging aspects emerge for BCI application related to acceptability and attractiveness [20]. Currently, therefore, the challenge is to create a device highly wearable, attractive, even inside a playful dimension, as well as reliable (namely, with accuracy of at least 75%, and latency of a few seconds) and moreover, trainingless. Based on previous experiences [21], lower accuracy levels determined relevant disengagement phenomena in some subjects with respect to the proposed exercise. The SSVEP could represent a suitable paradigm for simultaneously promoting the objectives of ergonomics, accuracy, and latency.

SSVEP is based on the following physiological principle: a person exposed to a flickering visual stimulus at a given frequency produces a corresponding cerebral potential in the occipital area at the same frequency. The limit in applications involving interaction with the real environment lies precisely in the massive use of the user's visual channel. AR technology allows to mix real and digital contents. Transparent glasses with an integrated display in the lenses represent a solution for the use of the SSVEP, by leaving partially free the view. The flickering stimulus is superimposed on the environment image without impeding direct vision. SSVEP allowed in a

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previous study the development of a highly wearable single-channel BCI/AR system for industrial environment, practically trainingless [21].

In this paper, an instrument for remote control of robot by wearable SSVEP-based BCI and AR glasses is proposed for rehabilitating children with ADHD. Effectively controlling the movements of a life-size robot through a new channel enhances rehabilitation engagement and effectiveness. In the following, the basic ideas and the architecture of the proposed instrument are highlighted in Section III. Then, Section IV reports the prototyping. In Section V, the metrological analysis is presented with the main aim of proving the decrease in real-time latency, by simultaneously keeping accuracy as high as possible. Then, in Section VI, the suitability for rehabilitation activities is proved by a case study at an accredited rehabilitation center.

II. Background

The application of robot technology in autistic children rehabilitation pointed out encouraging results [22], [23], [24] . The use of social robots [25],[26],[27] and [28] was proved to enhance attentional abilities and collaborative behaviors, also in rehabilitating children with ADHD [29]. The results of a study where High-Functioning Autism and ADHD children programmed Lego robots revealed that collaborative behaviors are strongly related to the enjoyment [30]. In Robot-Assisted Therapy, children are supported to sustain attention during a training task [18], [31]. Recently, a jumping and rolling spherical robot was implemented for treatment of ADHD and learning disability [32]. In these studies, robots support the execution of a task. In this paper, the robot enhances the treatment with BCI: the activity is made more engaging by offering immediate multisensory feedback to the attentional effort. BCI's role is central owing to its well-claimed capability of re-normalizing brain functional network topology [33]. The robot's role ancillary to BCI is peculiar in robot-based rehabilitation. In [34], a game-based training was proposed for ADHD children, with BCI and the humanoid robot NAO by Aldebaran Robotics. Main drawback was the long delay (15–20 s) between the command formation and its execution by NAO. Delay aversion, i.e. the motivation to escape or avoid delay, is a distinctive psychological process underlying the behavioral symptoms and cognitive deficits of ADHD disorder [35]. Some problems of attention were reported in [36]: a kid did not perform BCI task because he was attracted by the robot directly. In fact, the proposed set-up did not allow to watch at both the robot and the BCI stimulus simultaneously: children controlled the robot by looking at a pc display. Forcing a child to sit and fix a screen during a BCI exercise while a robot circulates around the room will worsen his attention levels. Therefore, it is important to allow the child to watch, approach, and follow the robot, without interrupting the BCI-based exercise.

III. Design

A. Basic Ideas

- *BCI for AR-based rehabilitation with robot:* A SSVEP-based single-channel BCI is integrated with a head-mounted display AR platform. The AR application target is a rehabilitation robot providing feedback to the patient remote control. The BCI channel enhances patient engagement and therapy effectiveness in critical applications of childhood-onset neuropsychiatric disorders, as ADHD. This allows to treat effectively arduous symptoms of persistent and impairing inattention, hyperactivity, and impulsiveness.
- *AR-BCI integration:* The integration of (i) the BCI instrumentation, consisting of EEG active dry electrodes and an acquisition unit, (ii) a pair of AR glasses, and (iii) an external processing unit, hosting BCI algorithms, allows to pilot the robot remotely by the SSVEP visual stimuli.
- *High-wearable BCI:* In a differential measurement of the SSVEP, the difference between the signal in the occipital and the frontal regions is usually considered, because the frontal region is not sensitive to the SSVEP response [21]. In the frontal region, the midline allows to maximize the distance to the occipital region. Some people are more sensitive to the SSVEP in the right rather than the left side of the occipital region [37]. In a trainingless system, the midline was chosen also to mitigate this difference. A single-channel BCI allows a high wearability, owing to the low number of EEG electrodes of a single differential measurement (two for the negative and the positive input, and one for the reference) and the miniaturization of the acquisition and processing units. Reducing the number of channels makes the activity of removing artifacts from eye movement and muscle contraction more challenging [38],[39]. If a single channel is used, this operation is even more complex [40]. The SSVEP paradigm represents a suitable choice also owing to its particular robustness to the artifacts caused by eye and muscle movement. In recent years, the use of dry electrodes helps to improve the wearability of EEG systems, avoiding the inconveniences of electrolytic gel [41]. The proposed solution involves customized dry active electrodes [42].
- *Robot for rehabilitation:* The robot plays the role of rehabilitation actuator, by giving also a feedback to the user in terms of movement and speech. This guarantees high levels of involvement to the patients, with a positive impact on the rehabilitation effectiveness.
- *EEG signals processing:* The BCI is based on Steady-State Visual Evoked Potential (SSVEP). By analyzing user's SSVEP, the proposed system is able to direct the Robot to the left, or to the right, with an angle of $\frac{\pi}{6}$ rad, $\frac{\pi}{4}$ rad, or $\frac{\pi}{2}$ rad.
  The SSVEP frequency is detected by a correlation algorithm in time domain. The EEG signal, after pass-band filtering, is compared with sinewaves at the same frequency of the visual stimulus, in order to detect the observed stimulus. The example of Fig. 1 highlights how the elicited SSVEP signal is correlated with the 12-Hz sinewave stimulus. The minimal spectral distance between the two bins of the available stimulus (10 Hz and 12 Hz) must be greater than the spectral resolution. Nevertheless, time windows lower than 0.5 s determine

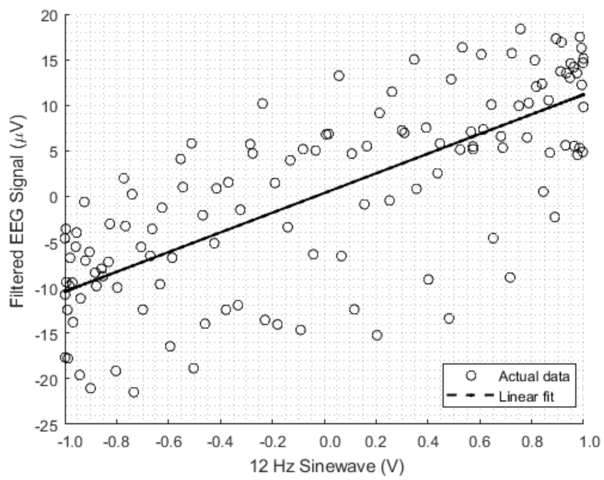

Figure 1: Scatter plot between filtered EEG signal and a 12 Hz sinewave

spectral resolution greater than 2 Hz. Therefore, the time window was minimized as possible to get a minimum latency beyond the constraint of the spectral resolution. To this aim, only two stimuli are used, in order to reduce the visual fatigue, increase the user attention and, thus, the accuracy of the BCI remote control. The number of available commands is increased using the eye blink artifacts detection. In particular, the commands of start, stop, and change direction are added. SSVEP and eye blink detection ensure the feature of a trainingless instrument, namely capable of working without any preacquired data from any untrained subject.

B. Architecture

The architecture of the BCI-AR instrumentation is shown in Fig. 2. In the *AR/BCI Integration Platform*, the AR *Glasses* renders the visual stimuli of the robot control menu, and elicits SSVEP responses in the patient. Then, in the *EEG Wearable Transducer*, the *Electrodes*, suitably placed on the scalp, sense

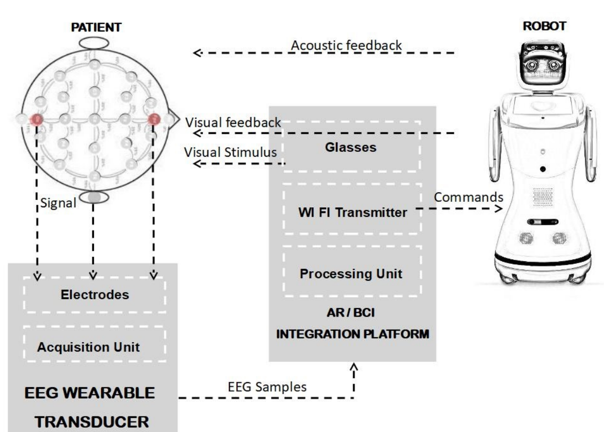

Figure 2: Architecture of the BCI-AR instrumentation.

Figure 3: The user starts the AR/BCI App on the AR glasses (red arrow) to control the robot remotely.

the EEG voltage to be digitized by the *Acquisition Unit*. Then, the EEG samples are sent to the *Processing Unit* (AR/BCI integration platform). After the processing, the response and the related command is sent to the robot by means of the *Wi-Fi Transmitter* (AR/BCI integration platform). In addiction to its movements, the robot provides also an acoustic feedback.

C. Operation

The user wears the AR glasses and, by the controller touchpad, launches the Android application AR/BCI App for rendering the flickering stimuli to pilot the robot (Fig. 3). By means of voluntary eye blinks, the user is able to set the three states of the robot (Fig. 4): *Idle State*, *Change Direction State*, and *Move Forward State*. As soon as the app is launched, the robot is in the state "Idle". With the first eye blink, the robot shifts to the state "Change Direction". Now, the user keeps a focus watch around one stimulus out of two, and makes the system send the desired command to the robot. As an example, the command can be "move to the right" or "move to the left", with an angle of $\frac{\pi}{6}$ rad, $\frac{\pi}{4}$ rad, or $\frac{\pi}{2}$ rad, by processing his/her corresponding SSVEP. When the direction is set, the user, by a second eye blink, make the robot move forward. A further eye blink makes, finally, the robot come back to the state "Idle".

IV. Realization

In the following, the realization of the proposed instrumentation is illustrated by detailing (i) the *feature extraction and processing*, (ii) the *hardware*, and (iii) the *software*.

A. Feature Extraction and Processing

- *SSVEP* Frequency Recognition: the frequency elicited by the observed stimulus is recognized by a correlation-based algorithm. Given a time window of duration *T*, the

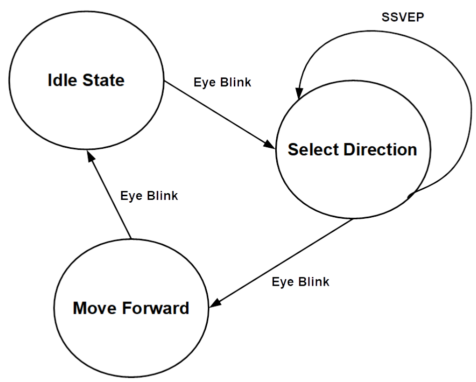

Figure 4: State machine for operating the instrument.

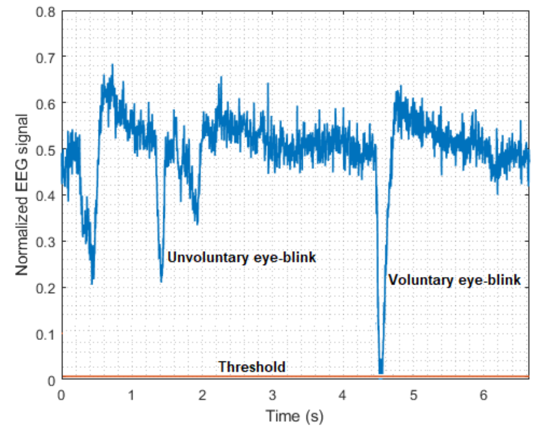

Figure 6: Detection of voluntary and involuntary eye blinks.

related signal fragment is filtered using a passband FIR filter between 5 and 25 Hz (Fig. 5). Then, the maximum values among the Pearson correlation coefficients ρ_1 and ρ_2 are assessed between the filtered data D_F and two sine waveforms Φ_1, and Φ_2, each one with a frequency of the corresponding flickering stimuli and variable phase ϕ:

$$\rho_1 = \max_{\phi \in [0,2\pi]} \frac{cov(D_f, \Phi_1(\phi))}{\sigma_{D_f}\,\sigma_{\Phi_1(\phi)}} \tag{1}$$

$$\rho_2 = \max_{\phi \in [0,2\pi]} \frac{cov(D_f, \Phi_2(\phi))}{\sigma_{D_f}\,\sigma_{\Phi_2(\phi)}} \tag{2}$$

Therefore, the following features are extracted

$$F1 = max(\rho_1, \rho_2) \tag{3}$$

$$F2 = \frac{max(\rho_1, \rho_2) - min(\rho_1, \rho_2)}{min(\rho_1, \rho_2)} \tag{4}$$

where D_f are the filtered Data, Φ_1 and Φ_2 the two sinewaves, ϕ is the phase, σ_D the standard deviation of the filtered data, and σ_Φ the standard deviation of the sinewave. Given two threshold values *T1* and *T2*, a signal fragment was marked as recognized if

$$F1 > T1 \quad \cap \quad F2 > T2 \tag{5}$$

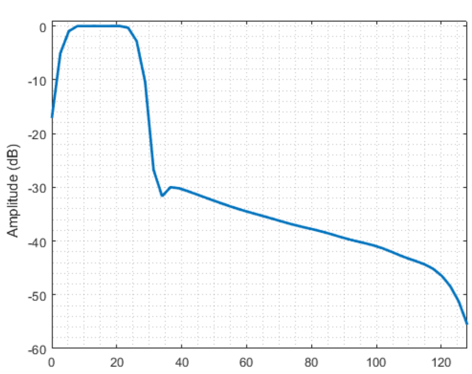

Figure 5: FIR Filter Amplitude frequency response.

If condition (5) is not satisfied, a new fragment of length *T*, overlapping with the previous one by *T/2*, is processed. The latency of this SSVEP detection algorithm, in terms of the response time of the system, is defined as the time interval necessary to recognize one of the two frequency values.

- *Eye blink detection:* artifacts arising from voluntary eye blinking are characterized by huge peaks along the EEG track. Such peaks are exploited to distinguish Voluntary and involuntary eye blinks when the signal exceeds a fixed threshold in normalized units, as shown in Fig.6.

B. Hardware

The hardware is shown is Fig.7.

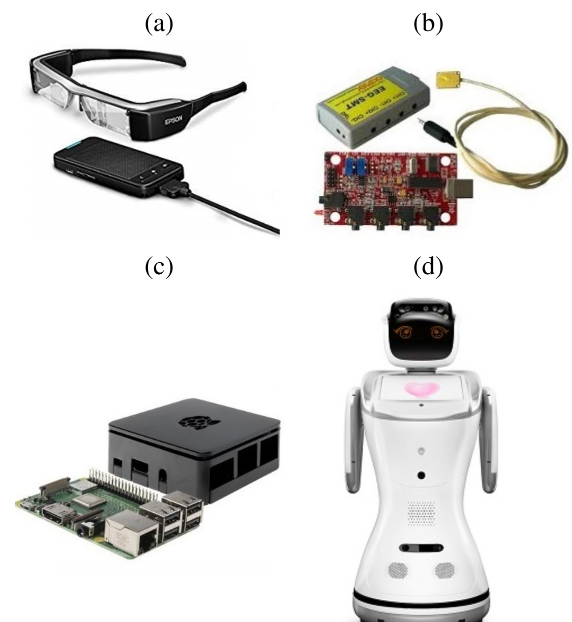

Figure 7: Hardware of the system: a) Moverio BT-200, b) Olimex EEG-SMT, c) Raspberry Pi 3, and d) Sanbot Elf.

- *Glasses:* The stimulation unit was developed using the Moverio BT-200 AR smart glasses (More info available at [43]). The perceived screen size of the glasses is 2 m at 5 m projected distance, with a refresh rate of 60 Hz. The AR environment consisted of two white arrows, related to the commands "move to the right" and "move to the left". Fig.8 show their positions at the right and left ends of the screen, respectively. The flickering frequencies were generated with the Android library OpenGL.
- *Acquisition Unit:* Brain signals were captured using (i) two active electrodes positioned at the Frontal Midline (Fpz), connected to the negative input, and Occipital Midline (Oz) positions, connected to the positive, according to the international system 10-20 [21], and (ii) a passive electrode (acting as reference) Driven Right Leg (DRL), positioned on the earlobe. The Fpz and DRL electrodes contacts consist of gold-plated, flat surfaces, while the Oz electrode was modified by adding eight gold-plated spring connectors to improve the skin contact through the hair. Signals were then digitized using the Olimex EEG-SMT, a 10-bit, 256 S/s, differential input Analog-Digital Converter (ADC) (More info available at [44]).
- *Processing Unit:* A single-board computer Raspberry Pi 3 More info available at [45] was used as processing unit and server, to provide the information extrapolated from the data received via USB from the Olimex. Each start of the acquisition was sent by the Moverio as soon as the Raspberry sent the related command to the robot.
- *Robot:* The target of this application was a SanBot Elf More info available at [46], a humanoid robot developed and produced by Qihan Technology Co. Such a robot is already used in rehabilitation, and the goal of this application was to direct the robot to the left, to the right, stopping it and making it move forward according to the user wishes, giving also a sonorous feedback about what it is going to do. The robot was connected trough Wi-Fi to the Raspberry Pi server, retrieving information in a JSON format.

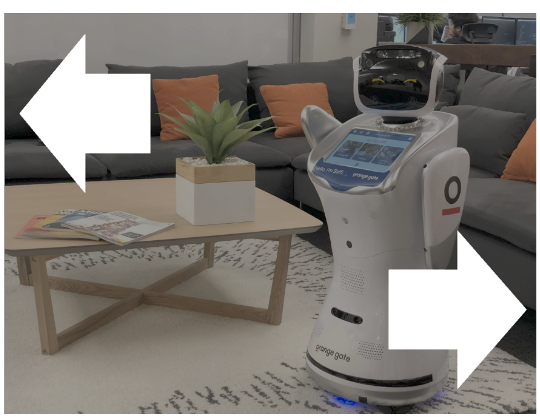

Figure 8: User perspective with the smart glasses: white arrows flicker for eliciting SSVEP.

C. Software

- *Moverio BT-200:* The Android application (more info available at [47]) home screen contains the buttons *Play*, *Connect*, and *Settings*. By pressing *Settings*, the arrow dimensions, the flickering frequencies, the positions on the screen, and the color can be configured. The menu *Connect*, once the Raspberry IP is added, allows to connect the Moverio to the Raspberry. By pressing *Play*, the user starts the flickering of the arrows and the subsequent EEG signal acquisition.
- *Raspberry Pi 3:* The software installed on the Raspberry Pi 3 is a software application in C, aimed at acquiring via UART the EEG signals digitized by the Olimex. The Baud Rate is set to 57600 bit/s, the packet size is equal to 17 bytes, and no parity bit was foreseen. Therefore, the Raspberry processes the EEG data as shown in Fig. 2. The Raspberry Pi 3 acts also as a Wi-Fi server, receiving from the Moverio the command of acquisition start, and sending to the robot the command related to the result of the processing.
- *Sanbot Elf:* On the robot Sanbot Elf, an Android application is installed for carrying out some tasks, in particular *go forward*, *stop*, *move to the right*, and *move to the left*, depending on the command in JSON format sent by the Raspberry. The application is run when the user inserts the IP Address assigned to the robot once connected to the Raspberry Wi-Fi. Therefore, he/she can press the Start button. Furthermore, from the app input interface, the rotation angle of the robot ($\frac{\pi}{6}$ rad, $\frac{\pi}{4}$ rad, or $\frac{\pi}{2}$ rad.), its speaking velocity, the word to be said if an obstacle is recognized, can be set.

V. Experimental Results

The SSVEP detection algorithm was characterized in terms of accuracy and response time. To this aim, brain signals of 20 untrained and healthy volunteers were analyzed by acquiring 24 brain differential signals per subject. The flickering frequencies were 10 Hz (on the right side of the screen) and 12 Hz (on the left). One of the main design goals is to avoid training; therefore, the stimulus frequencies of 10 Hz and 12 Hz were chosen according to the results of previous experimental campaigns [21], based on the studies reported in [48]. In particular, these two frequency values were chosen because sub-multiples of 60 Hz, the refresh rate of the Head Mounted Display Epson Moverio BT 200. For a flicker of 10 Hz, the stimulus reverses between black and white every three frames; a flicker of 12 Hz states in black for three frames and reverses to white for two frames [49]. Other frequency values could be obtained as a rounded (and therefore less accurate) average of a variable frequency stimulus [50]. Each subject was asked to focus on one stimulus at time, for 10 s. Further data were acquired, by leaving 10 users free to blink their eyes without focusing on any of the two stimuli. After processing the acquired data, the optimal values of the parameters for frequency and eye blink detection were found. Finally, an on-field analysis was carried out, by executing a given set of tasks with the robot.

A. Accuracy

- *SSVEP:* The accuracy has been defined as the percentage of correct responses on the total commands (percentage of correctly recognized values of frequency). A combination of parameters *T* and *T1* was used to evaluate the performance of the SSVEP algorithm. The data set was processed by using different time windows *T*: 0.4, 0.5, 0.8, and 1.0 s. For each of them, the features $F1$ and $F2$ were assessed. The luminosity of the environment was (97 $\pm$ 2) lx. The threshold value *T2* was fixed to 0.5, which means that the correlation with a sine waveform must be at least 50% greater than the other one. The threshold value *T1* was varied from 0.4 to 0.5 for each time window *T*. The resulting performance in terms of accuracy and response time is shown in Tabs. I, II, respectively. Several alternatives were investigated: for T1 over 0.5, the system accuracy does not increase significantly, while the latency goes up to 10 s. For T1 under 0.4 s, the accuracy goes down to 50% without a relevant decrease in latency.
  As visible from Tab. I and Tab. II, increasing *T1* increases the accuracy, but unfortunately also the response time. In Fig. 9, the trade-off between accuracy and time response is highlighted: the accuracy can be increased at the expense of response time. Actual data were fitted with a 2^{th} order polynomial function. For example, with a time response of (3.71 $\pm$ 0.92) s, an accuracy of 92.6% was achieved. An accuracy of 70.8% led to a time response decreasing to (0.64 $\pm$ 0.14) s. A time response of 1.5 s was selected as the final trade-off for clinical operation.
- *Eye blink detection:* In a previous exploratory experimental campaign, each voluntary eye blink reached zero value in normalized unit, i.e. determined as the EEG device output divided by its full-scale (fig. 6). Only very-few involuntary eye blinks reached the same zero value. According to a terminology usual in literature of classification tasks, therefore, a eye blink detection threshold equal to 0 guaranteed a perfect recall (no false negative) and a maximum precision (minimum false positives). The accuracy of eye blink detection was assessed by taking into account the number of voluntary eye blinks correctly recognized, the total count of voluntary eye blinks, the total count of involuntary eye blinks, and the number of involuntary eye blinks wrongly marked as voluntary. The luminosity of the environment was (147 $\pm$ 2) lx. To this aim, 10 subjects were considered. For each subject, at least a time window of 120 s of EEG signal was acquired, in order to capture at least 10 involuntary blinks [51]. After that, each subject was asked to voluntary blink the eyes for 10 times. In this way, for each subject, 10 voluntary blinks and 10 involuntary blinks were captured. Therefore, for each subject, the accuracy was assessed as follows:

$$A_{subject} = \frac{N_{blink} - E_{blink}}{N_{blink}} \cdot 100 \qquad (\%) \qquad (6)$$

  where N_{blink} is the total number of blinks, and E is the error count, that is when an involuntary eye blink is marked as voluntary, and vice-versa; then, the Accuracy ranges from 0% ($E_{blink} = N_{blink}$) to 100% ($E_{blink} = 0$). The accuracy of the eye blink detection algorithm is measured as (91.8 $\pm$ 3.7)%.
- *SSVEP/Eye blink integrated detection:* An evaluation of the accuracy of the system as a whole (AR/BCI/Robot) was carried out by means of a Java application for simulating the robot behavior. Such a Java application, running on a Personal Computer, receives the commands sent by the Raspberry and behaves in an equivalent way to the robot SanBot Elf. The luminosity of the environment was (147 $\pm$ 2) lx. 10 subjects were asked to make the virtual robot reach a target, moving it inside a maze, as highlighted in Fig.10. The minimum number of commands to bring the virtual robot out of maze successfully was estimated to be 14. The accuracy was assessed as:

$$A_{subject} = \frac{N_{commands} - E_{commands}}{N_{commands}} \cdot 100 \qquad (\%) \qquad (7)$$

  where $N_{commands}$ is the total number of commands sent, and $E_{commands}$ is the error count. The Accuracy ranges from 0% ($E_{commands} = N_{commands}$) to 100% ($E_{commands} = 0$). The threshold for eye blink detection

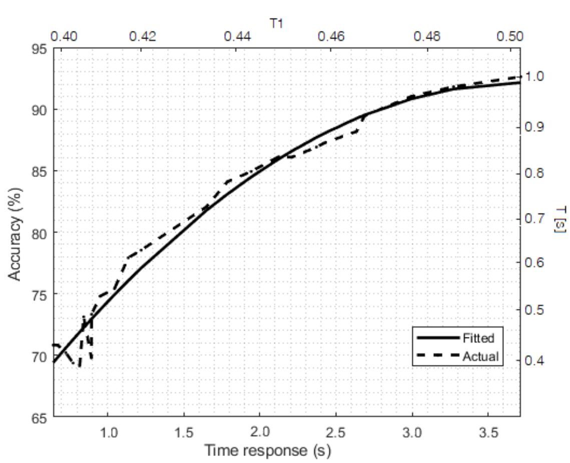

Figure 9: Trade-off between accuracy and time response highlighted in a plot vs parameters T1 and T.

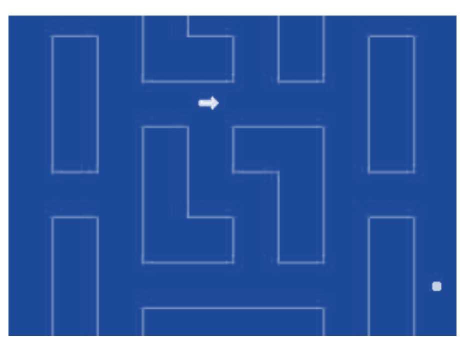

Figure 10: Java Application for simulating the behavior of the robot.

Table I: Accuracy (%) of SSVEP detection algorithm for different time windows T and threshold values T1

		T1					
		0.40	**0.42**	**0.44**	**0.46**	**0.48**	**0.50**
T (s)	**0.4**	70.8 ± 6.7	70.8 ± 6.7	70.2 ± 7.3	69.3 ± 7.5	69.1 ± 7.6	69.7 ± 8.1
	0.5	73.1 ± 8.2	73.3 ± 7.8	74.7 ± 8.0	75.4 ± 7.6	77.9 ± 7.1	78.5 ± 6.4
	0.8	82.0 ± 5.8	84.0 ± 5.8	84.9 ± 5.4	86.1 ± 5.0	86.9 ± 5.2	88.1 ± 4.8
	1.0	86.0 ± 4.2	87.2 ± 4.1	89.4 ± 4.1	91.0 ± 4.2	91.8 ± 3.7	92.6 ± 3.6

Table II: Time response (s) of SSVEP detection algorithm for different time windows T and threshold values T1

		T1					
		0.40	**0.42**	**0.44**	**0.46**	**0.48**	**0.50**
T (s)	**0.4**	0.64 ± 0.14	0.67 ± 0.15	0.72 ± 0.18	0.77 ± 0.19	0.81 ± 0.22	0.89 ± 0.26
	0.5	0.84 ± 0.18	0.89 ± 0.20	0.95 ± 0.22	1.04 ± 0.26	1.13 ± 0.31	1.22 ± 0.33
	0.8	1.65 ± 0.42	1.78 ± 0.45	1.94 ± 0.52	2.12 ± 0.56	2.37 ± 0.65	2.63 ± 0.73
	1.0	2.21 ± 0.54	2.41 ± 0.60	2.68 ± 0.69	2.99 ± 0.76	3.27 ± 0.84	3.71 ± 0.92

was set to 0 (normalized unit). The T and $T1$ were set to 0.50 and 0.44 s, respectively. The performance in terms of accuracy, time, and number of commands sent is shown in Tab. III.

B. Response time

The response time was assessed as Information Transfer Rate (ITR) [52], namely the amount of information conveyed by the system's output:

$$ITR = \left(log_2(N) + P\ log_2(P) + (1-P)\ log_2\left(\frac{1-P}{N-1}\right)\right)\frac{60}{T} \qquad (bit/min) \quad (8)$$

where N= 3 is the number of available decisions (two from the SSVEP recognition, and one from the eye blink detection), P the classification accuracy, and T the time response, shown in Tabs. I and II. In this application, ITR is maximum when T is equal to 0.4 s and $T1$ is equal to 0.40, with an accuracy of (70.8 ± 6.7)%, and time response of (0.64 ± 0.14) s, as shown in Tab. IV.

VI. Clinical ADHD Case Study

The preliminary on-field validation was carried out on 4 untrained children, from 6 to 8 years old, with different diagnosis always including ADHD. The robot was controlled by mapping the brain activity as follows:

- *10 Hz:* move to the right (with a rotation angle of $\frac{\pi}{4}$ rad);
- *12 Hz:* move to the left (with a rotation angle of $\frac{\pi}{4}$ rad);
- *Eye blink*: change State (move forward, stop, and change direction).

For this task, the parameters for SSVEP detection are the same of Tab. III. The untrained processing algorithms do not exploit previously acquired SSVEP response to improve classification. The luminosity of the environment was (151 ± 2) lx. The luminosity of the environment may afflict the system accuracy, because the Augmented Reality Smart Glasses exploit a see-through technology. When the flickering stimulus is turned off, the user can see normally the environment. Hence, more the environment is bright, less the flickering of the stimuli is visible for the user. This leads to a decrease in accuracy.

Each child had the task of piloting the robot in spaces progressively reduced in size, by achieving objectives each time differently positioned. For each child, the length of the trial was 10 min. The system was presented to the children making them be confident with both the eye blink and the SSVEP detection. Each child attended the trial of the other three. This overcame the initial resistance by two subjects, convinced to participate in the experiment led by the desire to emulate their companions. The aim of the experiment was:

- To verify the wearability and the usability of the device;
- To verify the level of the engagement elicited in the user;
- To evaluate the attentional performance.

Each child accepted to wear the electrodes and the smart glasses. Therefore, each child gave coherent commands to the robot for the entire length of the trial. None of the children interrupted the task before the end. Therapists and parents attended the experiment. For both of them the attentional performance exhibited by the participants were far superior to those expected on the basis on the previous experiences. For some of the participants the execution of a task for 10 continuous min was actually a completely new experience.

A short summary of the experiment results is shown in Tab. VI. In Tab. V, the proposed system is compared with two state-of-the-art BCI/robot solutions for children. Performance parameters mostly supporting the patient's attention were chosen [53]: (i) "accuracy to 2 s" and (ii) “mobility and see through”. In particular, "mobility” is the opportunity of physical proximity to the robot during the mental task execution. "See through" is the possibility of maintaining a visual contact with the robot. The robot, in fact, increases the user interest, but, at the same time, can distract with respect to the main task, if experienced as an alternative. Two other parameters, “wearability” (e.g. number of channels, dry electrodes) and “trainingless”, relate to the device acceptability, decisive for children under 8 years of age.

VII. Conclusions

A system, integrating augmented reality glasses with a non-invasive single-channel brain-computer interface based on SSVEP, is proposed for application in children ADHD rehabilitation. An untrained user can move a robot by focusing flickering stimuli and using eye blinking. The algorithm for feature extraction does not require training. The robot, after receiving the commands, gives acoustic and visual feedback to the user. The optical see-through AR technology allows to see the robot movements while looking at the visual stimuli simultaneously.

Table III: Performance of SSVEP/Eye blink integrated detection algorithm for T=0.5 s, $T1$=0.44, and eye blink threshold equal to 0.

SUBJECT	Time (s)	Commands	Errors	Accuracy (%)
#1	124.91	30	5	83.3
#2	217.76	57	12	78.9
#3	107.44	33	6	81.8
#4	94.67	23	5	78.2
#5	102.98	33	5	84.8
#6	195.53	51	11	78.4
#7	59.23	16	2	87.5
#8	95.04	26	2	92.3
#9	104.34	32	4	87.5
#10	142.55	41	7	82.9
AVERAGE	124,44 ± 30,72	34 ± 8	6 ± 2	83,5 ± 2,9

Table IV: ITR (bit/min) of SSVEP/Eye blink detection algorithm at varying time windows T and thresholds $T1$

		$T1$					
		0.40	0.42	0.44	0.46	0.48	0.50
T (s)	0.4	39.37	37.64	33.67	30.20	28.25	26.75
	0.5	33.86	32.25	32.66	30.65	31.80	30.46
	0.8	26.43	26.64	25.39	24.43	22.61	21.45
	1.0	23.43	22.46	22.16	21.23	20.06	18.27

Table V: Comparison of proposals in state of art in terms of 2-s accuracy, number of channels, lack of trained algorithm, and mobility.

	2-s Accuracy	Wearability	Trainingless	Mobility and See Through
[34]	$<$ 60 %	✓	✗	✗
[36]	n.a.	✗	✗	✗
Our proposal	$>$ 80%	✓	✓	✓

The system manages to overcome the main challenges posed today by the use of innovative strategies for the rehabilitation of children with ADHD. These challenges are related to acceptability and degree of involvement guaranteed by the proposed therapeutic setups. It has been observed that, at varying the time window T and the threshold $T1$ of the SSVEP detection algorithm, the related accuracy ranges from 70.8 to 92.6%, and the time response from 0.64 to 3.71 s, respectively, with an ITR ranging from 39.37 to 18.27 bit/min. As for the eye blink detection, the accuracy was estimated about 91.8% without latency.

A preliminary clinical case study at an accredited rehabilitation center on 10 healthy adult subjects highlighted an average accuracy of the SSVEP/Eye blink detection algorithm higher than 83%, with a corresponding time response of about 1.22 s and ITR up to 39 bits/min. Tests on 4 ADHD patients between 6 and 8 years old offered positive feedback on the device acceptance and attentional performance.

Table VI: Clinical case study: Performance of SSVEP/Eye blink integrated detection algorithm for T=0.5 s, $T1$=0.44, and eye blink threshold value equal to 0

Subject	Age (years)	Presence of parents	Initial reluctance
#1	6	yes	no
#2	7	yes	yes
#3	6	yes	yes
#4	8	no	no

In future work, several convolutional neural networks trained on each different user and able to achieve better ITR levels will be employed. The networks training will be guided by the voice-commands-based interaction user-robot.

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