A Wearable SSVEP BCI for AR-based, Real-time Monitoring Applications

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***Abstract*—A real-time monitoring system based on Augmented Reality (AR) and highly wearable Brain-Computer Interface (BCI) for hands-free visualization of patient's health in Operating Room (OR) is proposed. The system is designed to allow the anesthetist to monitor hands-free and in real-time the patient's vital signs collected from the electromedical equipment available in OR. After the analysis of the requirements in a typical Health 4.0 scenario, the conceptual design, implementation and experimental validation of the proposed system are described in detail. The effectiveness of the proposed AR-BCI-based real-time monitoring system was demonstrated through an experimental activity was carried out at the University Hospital Federico II (Naples, Italy), using operating room equipment.**

***Index Terms*—Augmented Reality, brain-computer interface, health 4.0, monitoring systems, operating room, real-time systems.**

I. Introduction

The 4.0 Era is based on the adoption of the enabling technologies typical of the Industry 4.0 paradigm (e.g., the internet of things [1], [2]; brain-computer interface [3]; artificial intelligence [4]; machine learning [5], [6]; cloud computing [7]; wearable technologies [8]–[11]; cyber-physical systems [12], [13]; augmented, virtual, and mixed realities [14]) in other contexts, with the aim to extend the advantages of the Smart Industry to other important application fields, such as healthcare, public administration, education and so on [15]. In particular, in the context of Health 4.0 revolution, Augmented Reality (AR) and Brain-Computer Interface (BCI) are among the technologies that are currently being used to implement innovative user-centered systems.

BCI is a direct communication pathway between human intentions and external devices, originally used in the field of motor disabilities or medical diseases [16]. However, in the last decade, BCI-based systems were also extended to entertainment, robotics and education [17]–[19].

The most used BCI paradigms include, it is important to mention (i) P300; (ii) Steady-State Visually Evoked Potentials (SSVEPs); (iii) Event-Related Potentials (ERPs); and (iv) Sensorimotor Rhythms (SMR). In particular, SSVEPs [20]–[22] are mostly used for practical systems, thanks to high levels of accuracy and reproducibility [23] often without the need of a training for the user [24], and optimal wearability. SSVEPs are induced in the primary visual cortex when observing intermittent visual stimuli, and preserve the periodicity of the external stimuli observed. This fixed frequency oscillation (usually within the band 8-15 Hz) allows an easier detection even in noisy conditions and with low electrodes [25].

Virtual Reality and AR head-mounted display (HMD) are optimal candidates for the generation of visual stimuli, since images are projected straight towards the eyes, increasing contrast, decreasing the distance between the user and the stimuli and, at the same time, reducing the noise factors of the surrounding environment.

The suitable combination of AR and BCI is already successfully implemented in the smart industry field [3], [26]. However, it is possible to extend the use of these technologies also to other application contexts, such as healthcare. AR is already largely employed as a fruition tool for a comprehensive set of information coming from medical equipment in operating room (OR). The integration of AR-based monitoring systems with SSVEP-based BCI can represent an interesting solution for hands-free user's input, providing an innovative way to have access to a set of information from the surrounding

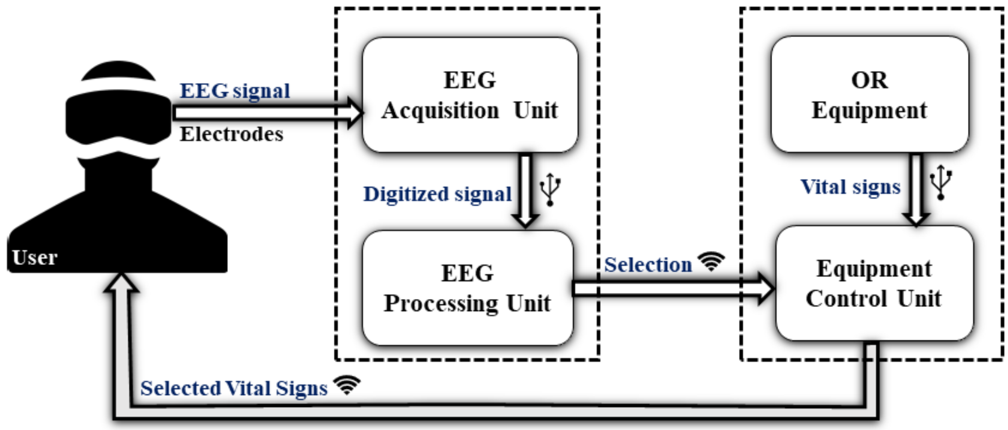

Fig. 1. System architecture of the proposed system.

environment.

The case study considered in this work is a typical scenario in OR, when the operators have to monitor patient's during medical procedures. The stringent requirements of health monitoring applications are addressed in [27]. Typically, any audio/video delay higher than 300 ms should be avoided to guarantee an acceptable and practical user experience. On the other hand, it is mandatory to guarantee a transmission accuracy as high as possible, by means of the realization of fault-tolerant systems and the adoption of safe communication protocols. For AR-BCI based applications, these requirements become even more stringent, to avoid phenomena such as motion sickness. Hence, it is important also to implement systems with high wearability and portability.

In this work a wearable, differential single-channel SSVEP-based BCI based is presented, wherein AR smart glasses are used with the twofold aim of (i) generation of the flickering stimuli and (ii) real-time visualization of the patient's vital parameters coming from the OR equipment. Off-the-shelf components (COTS) are used, together with dry and noninvasive electrodes, to acquire and process the EEG signal. Furthermore, the challenging possibility of using four flickering stimuli (rather than two as reported in [22], [25], [26]) is investigated, still preserving the current single-channel configuration and, at the same time, keeping high the performance in terms of accuracy and time response, also meeting the typical requirements of health monitoring applications.

The present paper is organized as follows. In Section II, the proposal is presented, focusing on the conceptual design of the AR-BCI integrated system. In Section III, the implementation of the system is described in detail. Section IV shows the results obtained during the experimental validation at the University Hospital Federico II. Finally, Conclusions are drawn.

II. Proposal

The design of the proposed AR-BCI based real-time health monitoring system is based on a highly wearable BCI adopting the SSVEP paradigm. In this way, AR is used both for displaying patient's vitals and for rendering the flickering stimuli needed to elicit SSVEP in the user's EEG. The proposed BCI represents a selection method to navigate the AR menu: in the considered case study, the brain-driven selection is used to display in AR the patient's vitals. The wearability of the system is guaranteed by the adoption of (i) AR Glasses; (ii) a single-channel differential configuration with few electrodes placed on the user' scalp; and (iii) portable acquisition and processing units.

A. Architecture

Figure 1 shows the System Architecture. An *Equipment Control Unit (ECU)* collects the patient vital signs from the *OR Equipment*. The user wears the *AR Glasses*, which render four flickering stimuli: the user looks at one stimulus (any of the four) and this corresponds to the selection of the desired vital sign to monitor. The *EEG signal* is acquired by means of EEG *Electrodes*; then, it is digitized by the *EEG Acquisition Unit*, which sends the data to the *EEG Processing Unit*. The EEG signal is then processed and the results is sent to the *ECU*. Finally, the patient's vitals (as selected) are sent to the AR Glasses which display them. In this way, the operator is able (i) to select in real-time the vital signs to display, and (ii) to monitor the patient's vitals without having to constantly look at the medical equipment.

B. SSVEP processing

A time-domain correlation-based algorithm is used to detect the frequency elicited by the observed flickering stimulus (in the range 8-15 Hz) [25].

Considering an EEG signal of length T (typically from 0.5 to 2.0 s), the first step is a passband FIR filtering between 5 Hz and 25 Hz. Therefore, the Pearson correlation coefficients ρ_i are assessed between the filtered data D_f and four sine waveforms Φ_i, where i=*1 ... 4*, at the same frequency of the corresponding flickering stimuli and variable phase θ:

$$\rho_i = \underset{\theta \in [0, 2\pi]}{max} \frac{cov(D_f, \Phi_1(\phi))}{\sigma_{D_f}\, \sigma_{\Phi_i(\phi)}} \quad (1)$$

where D_f are the filtered data; Φ_i are the i^{th} sinewaves; θ is the phase; σ_D is the standard deviation of the filtered data; and σ_{Φ_i} the standard deviation of the sinewaves. The following features are then extracted:

$$F1 = 1^{st} \underset{i \in [1,4]}{max} (\rho_i) \quad (2)$$

$$F2 = 2^{nd} \underset{i \in [1,4]}{max} (\rho_i) \quad (3)$$

$$F3 = \frac{F1 - F2}{F2} \quad (4)$$

$F1$ represents the maximum value among the correlation coefficients assessed for all the four frequencies of stimuli; $F2$ is the second largest correlation coefficient for the remaining three stimuli; and, finally, $F3$ represents the relative difference between $F1$ and $F2$.

Given two threshold values *th1* (usually from 0.40 to 0.60) and *th2* (usually from 0.5 to 1.0), a signal fragment can be marked as recognized if the following condition is satisfied:

$$F1 > th_1 \quad \cap \quad F3 > th_2 \quad (5)$$

If condition (5) is not satisfied, a new EEG signal of length *T*, overlapping with the previous one by *T/2*, is processed.

An offline analysis of the SSVEP dataset was carried out aiming to evaluate the performance in terms of correctness of classification and time response of the algorithm. With respect to [25], the effect of the frame rate drop during the generation of the flickering stimuli was taking into account. In fact, a shift in the frame-rate inevitably translates into a consequent shift of the stimuli frequency, decreasing the accuracy of classification. Considering $N_{signals}$ as the total number of signals and *E* as the number of errors during classification, the accuracy A is defined as:

$$A = \frac{N_{signals} - E}{N_{signals}} \cdot 100 \quad (6)$$

where the numerator indicates the number of signals correctly classified, and A is expressed as a percentage.

On the other hand, the time response is the time needed by the algorithm to classify a signal fragment.

It should be mentioned that higher is the value chosen for the aforementioned parameters (*T, th1* and *th2*), the better the goodness of classification obtained; however, the time needed to the system to make a decision increases.

Brain signals of 20 healthy and untrained subject were analyzed, with 24 brain signals per volunteer, using Epson Moverio BT-200 AR glasses as generators of the flickering stimuli. The luminosity of the environment was (97 $\pm$ 2) lx. In this dataset, two stimuli were used, at a nominal frequency of 10.0 Hz and 12.0 Hz. Each subject was asked to focus for 10 s on one stimulus at time. After the collection of all the acquired data, a frame rate analysis was carried out, obtaining an average frame rate of about 59.0 Hz instead of the nominal 60.0 Hz. Consequently, the stimuli frequency shifted (i.e. from 12.0 Hz to 11.8 Hz).

By taking into account this shift, the new performances were evaluated and compared with the results reported in [25]. Table I summarizes the difference between the two algorithms, with a focus on the performance for *th1, th2* fixed to 0.5.

The current accuracy and time response values were measured at 3-σ (99.7% confidence level), obtaining a level of accuracy higher than 93 % with about 3.4 s of time response.

TABLE I
DIFFERENCES BETWEEN THE PREVIOUS [25] AND CURRENT SSVEP DETECTION ALGORITHM WITH *th1, th2 = 0.5*

Parameters	Quantity	Previous [25]	Current
T = 0.5 s	**Accuracy (%)**	78.5 $\pm$ 6.4	79.6 $\pm$ 9.7
//	**Time response (s)**	1.22 $\pm$ 0.33	1.23 $\pm$ 0.13
T = 0.8 s	**Accuracy (%)**	88.1 $\pm$ 4.8	91.0 $\pm$ 6.2
//	**Time response (s)**	2.63 $\pm$ 0.63	2.54 $\pm$ 0.27
T = 1.0 s	**Accuracy (%)**	92.6 $\pm$ 3.6	93.8 $\pm$ 6.0
//	**Time response (s)**	3.71 $\pm$ 0.92	3.42 $\pm$ 0.31

III. IMPLEMENTATION

In this section, the implementation of the proposed system is described. More details are given about (i) the ECU; (ii) the OR Equipment; and (iii) the AR-BCI Integrated System, focusing also on the communication between the devices.

A. Hardware

1) ECU: The used *ECU* is a laptop with 16 GB RAM, and two USB 2.0 ports, used for the communication with the *OR Equipment*. The WiFi *IEEE 802.11a/b/g/n* is employed for the wireless communication with the EEG Processing Unit.

2) OR Equipment: Two electromedical instruments were used for the implementation of the system [28]:

- a ventilator (Drager Evita Infinity V500 [29]), equipped with a LAN interface and three serial Interfaces, with the possibility to fetch the parameters using the MEDIBUS protocol at different Baud Rates.
- a patient monitor (Philips IntelliVue MP90 [30]), equipped with a LAN interface; data can be collected in real-time only by means of a dedicated proprietary software, namely *Medicollector*.

3) AR-BCI Integrated System: The AR-BCI Integrated Systems includes a set of AR Glasses, an EEG Acquisition Unit and, finally, an EEG Processing Unit.

- *AR Glasses:* Epson Moverio BT-350 [31] (Fig. 2-a), an AR optical see-through (OST) device with a 30 Hz nominal refresh rate; an angle of view of 23 degrees diagonally; and a *720p* display.
- *EEG Acquisition Unit:* Olimex EEG-SMT [32] (Fig. 2-b), a 10 bit, 256 Sa/s Analog to Digital converter. Three dry electrodes are placed on the user scalp in a single-channel differential configuration. The two active electrodes are placed in position Oz, Fz (according to the 10-20 International System [25]) and connected respectively to the CH+ and CH- of the Olimex. Then, a passive electrode is

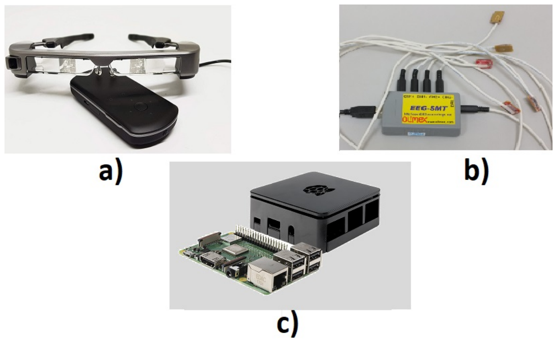

Fig. 2. AR-BCI Hardware: a) Epson Moverio BT-350; b) Olimex EEG-SMT; c) Raspberry Pi 3.

placed on the earlobe and connected to the Driven Right Leg (DRL) channel, aiming to reduce the common mode interference.

- *EEG Processing Unit:* the portable EEG Processing Unit chosen is the Raspberry Pi 3 [33] (Fig. 2-c), a single-board computer equipped with LAN, USB, HDMI interfaces. The Raspberry receives via UART the signal digitized by the Olimex and, after the processing, sends to the ECU the results.

B. Communication

The communication between all the devices was handled by implementing a dedicated software.

- *ECU-Equipment:* a script in MATLAB environment was implemented on the ECU to collect the data from the OR Equipment. A subsection of this code realized the MEDIBUS protocol, to configure and receive in real-time the ventilator parameters over serial interface, by means of a RS232-USB adapter. Furthermore, a second subsection was developed exchanging data with *Medicollector*, the software that acquires in real-time the waveforms coming from the monitor. After Medicollector is running on the ECU, the MATLAB code receives in real-time the desired Monitor waveforms over TCP/IP protocol by means of the *Medicollector* adapter, a particular LAN-USB adapter.
- *EEG Acquisition Unit-Processing Unit:* once the EEG signals is acquired and digitized by the EEG Acquisition Unit, data are sent to the EEG Processing Unit via UART through USB interface, by means of a software written in C and installed on the Processing Unit. The software also acts as a TCP Client, sending to the ECU (acting as TCP Server) the result of the processing.
- *EEG Processing Unit-ECU:* a TCP Server was implemented and integrated on the ECU in MATLAB with the code related to the acquisition of the vital signs from the OR equipment. The TCP Server establishes the communication with the EEG Processing Unit to receive the results of the processing over TCP/IP protocol. Therefore, the Laptop sends to the Glasses the parameters according to the user selection.

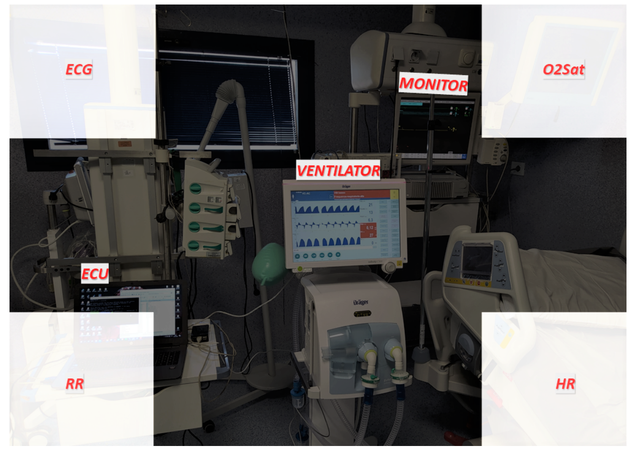

Fig. 3. User's view during the selection by BCI. Reprinted from [28], Copyright 2021, with permission from Elsevier.

- *ECU-Glasses:* the afore mentioned TCP Server is also used to communicate with the AR Glasses. The ECU (TCP Server) sends only the parameters selected by BCI to the user over TCP/IP protocol. An Android application was realized on the Glasses to receive over TCP/IP protocol the vital signs, and display them in real-time.

IV. Case Study

First, the frame rate drop related to the generation of the flickering stimuli was assessed. Then, the on-field results related to SSVEP classification accuracy and time response with four stimuli were obtained. Finally, the delay regarding the real-time acquisition and visualization of the vital signs coming from the OR equipment is measured and compared with the aforementioned typical monitoring systems requirements.
Fig. 3 shows a picture of the user point of view while wearing the AR Glasses, with the OR Equipment in background. Four flickering stimuli at the edges of the display are visible. By looking at any of the stimuli, the user can select the vital sign to be displayed among four different choices: electrocardiogram *(ECG)*, oxygen saturation *(O2Sat)*, hearth rate *(HR)* and respiration rate *(RR)*.

A. Preliminary AR-BCI Functional Validation

Before acquiring the SSVEP signals, the frame rate drop produced by the application running on the AR Glasses was measured, obtaining an average frame rate of about 32 fps, higher than the nominal 30 Hz. This leads to the presence of undesired multiple frames. The classification algorithm was modified accordingly taking into account the average fps obtained. Fig. 4 shows what the user sees after selecting the ECG waveform by SSVEP. The user sees the main parameters from the ventilator (i.e., Compliance *Cdyn*, the Minimum, Mean, and Peak Airway Pressure *Pmin*, *Pmean*, and *PIP*, the Minute Volume *MV*, and the Spontaneous Expired Total Volume *VTespon*). At the bottom, the real-time variation of

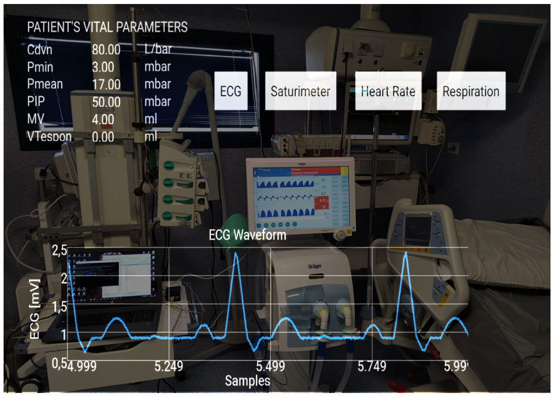

Fig. 4. User's view during the visualization of the patient's vitals. Reprinted from [28], Copyright 2021, with permission from Elsevier.

TABLE II
RESULTS OF SSVEP PROCESSING FOR EACH RUN DURING THE EXPERIMENTAL SESSION

#Run	Frequency [Hz]	[0-2 s]	[2-4 s]	[4-6 s]
#1	8 Hz	✓		
#2	10 Hz		✓	
#3	12 Hz		✓	
#4	15 Hz			✓
#5	8 Hz	✓		
#6	10 Hz	✓		
#7	12 Hz			✗
#8	15 Hz		✗	
#9	8 Hz		✓	
#10	10 Hz			✗

the selected vital sign coming from the monitor (in this case, the ECG) is displayed.

B. Experimental characterization of the SSVEP performance

After the validation of the AR-BCI functionalities of the system, the on-field SSVEP performance were evaluated. The four flickering frequencies chosen to let the user select the waveforms coming from the patient monitor are 8 Hz, 10 Hz, 12 Hz and 15 Hz.

Table II summarizes the user's choices, with the related time response of the algorithm. It can be noticed that, in three cases, the algorithm could not recognize the correct frequency observed.

As shown in Table III, the frequency value that showed the best performance in terms of both accuracy and time response was 8 Hz, since highest frequencies are more sensitive to the frame rate variations. For instance, a frame rate drop from 32.0 Hz to 30.0 Hz leads to frequency shift from 15.0 Hz to 14.1 Hz, and from 8.0 Hz to 7.5 Hz. Therefore, the higher probability to correctly detect the stimuli is at 8 Hz, 10 Hz, rather than at 12 Hz, 15 Hz. The luminosity of the environment (147 ± 2) lx and the presence of four squares instead of two, also contributed to the drop of the overall accuracy with respect to the results obtained offline. After the selection through BCI, the vital signs are displayed on the AR Smart Glasses.

TABLE III
SUMMARY OF SSVEP PERFORMANCE AFTER THE EXPERIMENTAL SESSION

Frequency [Hz]	Accuracy [%]	Time response [s]
8 Hz	100.0	2.67
10 Hz	66.7	4.00
12 Hz	50.0	5.00
15 Hz	50.0	5.00
Total	**70.0**	**4.00**

C. Evaluation of the system transmission

The experimental session consisted in 10 runs. Since the Medicollector was used in free-trial mode, each run had a maximum duration of 180 s. For each run, the time interval necessary to display on the Glasses the selected data received by the Laptop over TCP/IP protocol was assessed, by means of the MATLAB stopwatch timer *tic*. At the end of the session, the mean value at the 3-sigma uncertainty were evaluated. The TCP/IP delay measured was $(10{\pm}3){\cdot}10^{-4}$ s, a value that fully satisfied the requirements reported in [34], [35].

V. CONCLUSION

An integrated, wearable BCI-AR based real-time monitoring applications was proposed. By means of the integration of AR with BCI (employing the SSVEP paradigm), the user can select hands-free which data to display in AR. As a case study, the real-time visualization of patient's vitals in OR was considered. The data were collected from the OR equipment, and displayed in real-time on the user's AR glasses. The user could select by brain activity which parameter should be displayed and monitored.

After a preliminary validation, which ensured the working functionalities, the SSVEP accuracy and time response, along with the data transmission delay, were measured, demonstrating the effectiveness the proposed monitoring system. In particular, it was observed that the measured delay introduced by the Android application to receive the vital signs is negligible, preserving the real-time requirements and confirming the improvement of AR in the Health 4.0 framework. The on-field characterization of the single-channel SSVEP-based BCI with four flickering stimuli showed an accuracy of 70% with a latency of approximately 4.00 s.

Further work will be dedicated to improve the SSVEP-detection algorithm, also introducing a time-frequency analysis to mitigate the effects caused by the frame-rate drop and, thus, improve the classification accuracy.

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