Multimodal feedback in assisting a wearable brain-computer interface based on motor imagery

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***Abstract*—A multimodal sensory feedback was exploited in the present study to improve the detection of neurological phenomena associated with motor imagery. At this aim, visual and haptic feedback were simultaneously delivered to the user of a brain-computer interface. The motor imagery-based brain-computer interface was built by using a wearable and portable electroencephalograph with only eight dry electrodes, a haptic suit, and a purposely implemented virtual reality application. Preliminary experiments were carried out with six subjects participating in five sessions on different days. The subjects were randomly divided into "control group" and "neurofeedback group". The former performed pure motor imagery without receiving any feedback, while the latter received multimodal feedback as a response to their imaginative act. Results of a cross validation showed that at most $61\,\%$ of classification accuracy was achieved in performing the pure motor imagination. On the contrary, subjects of the "neurofeedback group" achieved up to $82\,\%$ mean accuracy, with a peak of $91\,\%$ in one of the sessions. However, no improvement in pure motor imagery was observed, either when practicing with pure motor imagery or with feedback.**

***Index Terms*—brain-computer interface, motor imagery, electroencephalography, extended reality, neurofeedback, wearability, dry elecrtrodes.**

I. Introduction

Motor Imagery (MI) is widely exploited in building Brain-Computer Interfaces (BCIs). Indeed, when imagining the movement of a body part, the associated neurological phenomena can be measured and translated into a command to control an external device [1]. Moreover, imagined movements are linked to the conscious activation of brain areas that are also involved in the preparation and execution of a movement. For these reasons, MI-based BCIs are increasingly exploited in neurorehabilitation [2], but also in sports, music, and gaming [3], [4], [5], [6], [7]. Application examples consist of using a word processing system, driving a wheelchair, controlling a robotic limb, or navigating 2D and 3D environments.

When detecting MI, the adopted processing algorithms rely on the detection of “event-related desynchronization" and “event-related synchronization" phenomena in the μ (about $8\,\mathrm{Hz}$ to $12\,\mathrm{Hz}$) and β (about $13\,\mathrm{Hz}$ to $30\,\mathrm{Hz}$) bands, whose spatial localizations depend on the specific MI task [8]. However, these phenomena have great variability across subjects and across different sessions even for the same subject. This implies poor reproducibility of system performance. Therefore, in such a context, neurofeedback (NF) aids the user in the self-regulation of brain rhythms and promotes neural plasticity [9]. In details, a sensory feedback is delivered to the user as a result of real-time processing of his/her brain signal. This aims to reduce the training time needed to use the interface by actively engaging the user of the system.

Regarding brain signals acquisition, a non-invasive, wearable, and possibly portable neuroimaging technique is the electroencephalography (EEG) [10]. Due to its advantages, BCIs are often based on EEG by typically using more than 10 wet electrodes [11], [12], [13]. Unfortunately, such a setup would require excessively long preparation time for the user and discomfort due to the usage of conductive gel. Therefore, with the aim to increase the usability of BCI technologies by end users, EEG devices relying on dry electrodes have been investigated [14]. Indeed, dry electrodes measure EEG signals by directly touching the scalp without the use of gel. However, they are associated with high and unstable contact impedances, which results in signals with low signal-to-noise ratios [15], [16].

Some studies have attempted to solve such issues and they even evaluated whether system performance decreased when using dry electrodes in MI-based BCIs [17], [18], [19], [20]. In particular, literature suggests that dry and wet electrodes lead to compatible classification accuracies [21]. Further evidence has shown that deep learning approaches are promising in building robust systems with dry electrodes [22]. Finally,

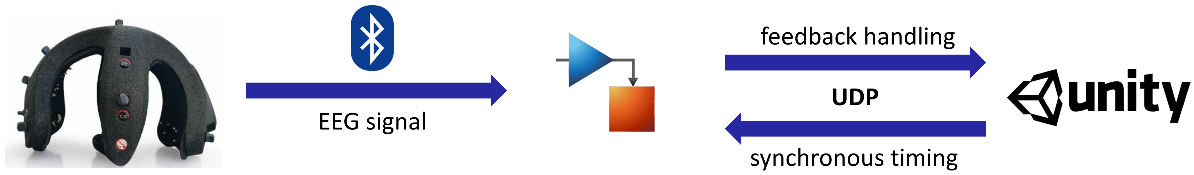

Figure 1: Block diagram of the proposed system. EEG: electroencephalography, UDP: User Datagram Protocol.

spectral power measures during rest in the $4\,\mathrm{Hz}$ to $50\,\mathrm{Hz}$ range were also found to be compatible in both wet and dry systems [23]. This would imply that dry electrodes should be even useful in measuring phenomena in the frequency ranges associated with MI. Nonetheless, the use of dry electrodes in MI-BCI appears still limited.

Upon these considerations, the present study proposes a wearable MI-based BCI system relying on an EEG device with only eight dry electrodes. A multimodal NF is investigated within such a system in order to improve the detection of left hand and right hand MI over 5 experimental sessions. In aiming to evaluate how much the feedback is assisting the system functionality, a control group was also taken into account, i.e. some subjects did not receive the NF. Hence, Section II presents the materials and methods used in implementing and testing the system, while Section III discusses the preliminary results associated with motor imagery detection.

II. Materials and methods

The block diagram of the proposed system is shown in Fig. 1. EEG signals are acquired and sent through Bluetooth to the processing module, whose output drives the eventual feedback. The feedback application also dictates the timing for the execution of the MI tasks, namely the system operates synchronously. Details are reported in the following subsections per each block.

Figure 2: Wearable and portable electroencephalograph by ab medica.

A. EEG acquisition

EEG signals were acquired by using the *Helmate* device by ab medica® [1] (Fig. 2). Along with its dedicated software, this is a device for acquiring, displaying, and analyzing EEG signals. It is a Class IIA device certified according to the Medical Device Regulation (EU) 2017/745 and it consists of eight single-ended channels. A total of 10 dry electrodes (channels plus reference and bias) are employed and different shapes are available to overcome the hair and reach the skin. According to the international 10-20 EEG system [24], channels are located at FP1, FP2, Fz, Cz, C3, C4, O1, and O2, while the reference and bias electrodes are placed in the frontal region at AFz and FPz, respectively. The quality of electrode-skin contact can be checked too through the software, which implements a contact quality check. For each electrode, the optimal numerical value associated with contact quality is set to be below 100, though a value below 200 is already acceptable. Notably, this value does not directly represent the impedance measurement but is rather an index. In the proposed setup, data were collected at a sampling rate of $512\,\mathrm{Sa/s}$ and transmitted via Bluetooth to a custom Simulink model.

B. EEG processing

In order to drive the feedback, the EEG signals were processed and its features extracted by means of the Filter Bank Common Spatial Pattern (FBCSP) [25]. Although this approach was proposed about 10 years ago, it still remains one of the most popular and stable algorithm in binary EEG-based BCIs [26], [27]. The mutual information-based best individual features (MIBIF) was employed in conjunction with FBCSP to select the most significant features, while the Naive Bayesian Parzen Window (NBPW) was employed as classifier. This returns the class to which the EEG signals belong (e.g., right or left) and the probability associated with that class.

In driving the feedback, EEG signals had to be processed online. Therefore, this algorithm was implemented in Simulink. In there, the class and the probability returned by the classifier were sent to Unity via User Datagram Protocol (UDP), so as to modulate the feedback direction and intensity.

C. Multimodal feedback

With the aim of improving the detection of MI and speed up the user training, multimodal feedback is proposed. Visual and haptic feedback modalities were simultaneously provided to the users as a consequence of their mental task. The feedback were managed through an application developed with Unity[2].

The visual feedback consisted of a ball rolling left or right on a virtual floor. Two white lines were set as targets on the

[1]https://www.abmedica.it/

[2]https://unity.com/

two sides of this scenario (Fig. 3). Starting from the center, the ball's movement could be modulated in terms of direction and applied force. The virtual environment was delivered through a PC monitor.

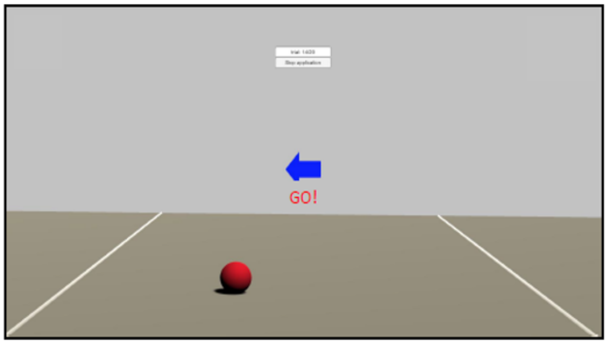

Figure 3: Visual feedback in the virtual scene.

Instead, the haptic feedback was provided by means of *TactSuit X40* from bHaptics Inc [3] (Fig. 4). This is a wearable and portable haptic vest equipped with 40 individually controllable vibrotactile motors. The vibration can be modulated in terms of duration, frequency, and intensity. In the current proposal and in accordance with the movement of the virtual ball, the vibration started from the center of the torso (front side) and it could be moved to the left or to the right. The class probability could modulate the position and the intensity of the vibration. The suit was controlled via Bluetooth through the Unity application.

Figure 4: Vibrotactile suit by bHaptics Inc.

D. Experimental paradigm

Preliminary experiments were carried on with the described system. The experiments involved participant in five experimental sessions over five weeks. Each session lasted about one hour. Participants were divided into two groups, namely the "control group" and the "neurofeedback group". In both cases, they were asked to imagine the movement of the left hand or the right hand. In the former group, each session included only pure motor imagery. In the latter group, instead, each session included both the pure motor imagery phase with the aim of training the algorithm, and a subsequent online phase, where EEG signals were processed to drive the feedback. In any case, a synchronous paradigm was adopted, i.e. the user had to imagine according to an external cue.

For the pure motor imagery, the Unity application only indicated the timing. For each trial it sequentially showed a fixation cross for $2.00\,\mathrm{s}$, a cue (i.e., a left or right arrow) between the time instants $t = 2.00\,\mathrm{s}$ and $t = 3.25\,\mathrm{s}$, the word "GO!" up to $6.00\,\mathrm{s}$, and the word "RELAX" lasting from $1.00\,\mathrm{s}$ to $2.00\,\mathrm{s}$ (Fig. 5). Participants were only asked to prepare to imagine the movement during the cue, and then to actually imagine when the "GO!" was displayed. The relax at the end was instead randomized in order to avoid any bias between consecutive trials. One run consisted of 30 trials, randomized between the left and right sides. Three or six of such runs were recorded for the neurofeedback and the control groups, respectively.

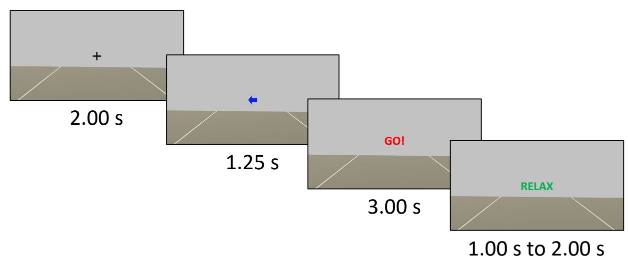

Figure 5: Timing of a single trial for the pure motor imagery phase.

On the other end, the first three runs for the neurofeedback group were exploited to train the online subject-dependent model. This was used in the last three runs. In identifying that model, a cross-validation technique was used for selecting the best time window in terms of optimal classification accuracy during the MI task. For this purpose, a sliding window of $2.00\,\mathrm{s}$ with a shift of $0.25\,\mathrm{s}$ in the MI window was adopted. Once the model was identified, participants underwent further three runs during which they received feedback in response to the MI task. The timing scheme was similar to the previous one, with two exceptions: the participants started to imagine in correspondence of the cue and they received the feedback from $4.50\,\mathrm{s}$ to $6.00\,\mathrm{s}$. No "GO!" or "RELAX" text was displayed this time, but the only arrow to indicate the task. A $2.00\,\mathrm{s}$-wide sliding window with $0.25\,\mathrm{s}$ shift was used to process the EEG signal online with the FBCSP approach. Participants were instructed to try moving the ball over the white lines of the game environment, which also corresponded to maximum activations of the vests' haptic feedback at the rear of the respective side.

[3]https://www.bhaptics.com/tactsuit/tactsuit-x40

III. Results

The results of the preliminary experiments are reported in this section. First, the subjects participating in the experiments are described. Then, the performance of the proposed system are discussed.

A. Subjects

Six right-handed healthy volunteers (four female and two male, age 26 $\pm$ 2) participated in the preliminary experiments. They were randomly divided into "control group" (S01, S02, S03) and "neurofeedback group" (S04, S05, S06). Subjects S01 and S03 had previous experience with motor imagery paradigm, S02 and S05 had previous experience with multiple BCI paradigms. The remaining two subjects had never used a BCI before. Prior to the beginning of the experiments, subjects were asked to try to imagine different hand movements (e.g. squeezing an object, snapping fingers) by testing internal visual, external visual and kinesthetic imagery. Once they chose the one they were most confident with, they were asked to keep it constant throughout the session. The study was approved by the Ethical Committee of Psychological Research of the Department of Humanities of the University of Naples Federico II. Information about the experimental protocol was provided to the participants and they were asked to read and sign an informed consent form.

B. System performance

First results were obtained in terms of best classification accuracy during the MI window using a 5-fold cross validation with 10 repetitions. As mentioned before, a $2.00\,\mathrm{s}$-wide sliding window with $0.25\,\mathrm{s}$ shift was exploited in the MI window for both groups and both phases (i.e. pure motor imagery and motor imagery with feedback). The optimal $2.00\,\mathrm{s}$-wide window was selected as the one that simultaneously maximizes the classification accuracy and minimizes the difference between accuracies per class.

Fig. 6 and Fig. 7 show the results obtained by the "control group" and the "neurofeedback group", respectively, during the pure motor imagery phase of each experimental session. The subjects participating in the experiments are reported on the x-axis, and for each of them the five sessions are shown. The mean classification accuracy is instead reported in percentage on the y-axis. In both cases, no training effect is evident, i.e. classification accuracy is not increasing across sessions. Moreover, all the accuracies remain below $60\,\%$ throughout the sessions.

Fig. 8 and Fig. 9 show the results obtained by the "control group" and the "neurofeedback group", respectively, during the second phase of each experimental session. It is useful to remark that, while the control group repeated pure motor imagery, the neurofeedback group received feedback as a response to the imaginative act. In the former case, the results are similar to the previous ones and S01, S02, and S03 reached $58\,\%$, $61\,\%$, and $56\,\%$ average classification accuracy across the sessions, respectively. In the latter case, when subjects received the online feedback, there is a substantial

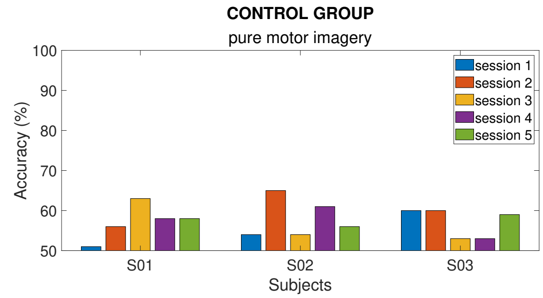

Figure 6: Mean accuracy over the sessions for the "control group" during the first part of the session of pure motor imagery.

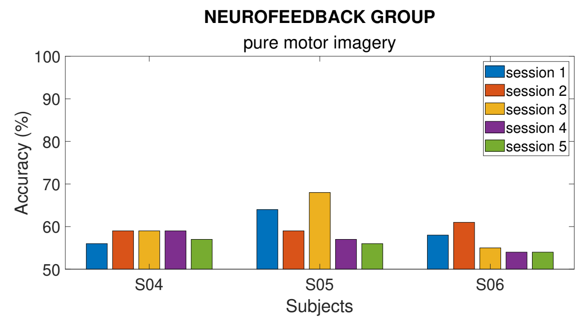

Figure 7: Mean accuracy over the sessions for the "neurofeedback group" during the first part of the session of pure motor imagery.

improvement in classification accuracy. These subject reached up to $91\,\%$. In details, S04, S05, and S06 obtained an average during the sessions of $75\,\%$, $82\,\%$, and $59\,\%$, respectively.

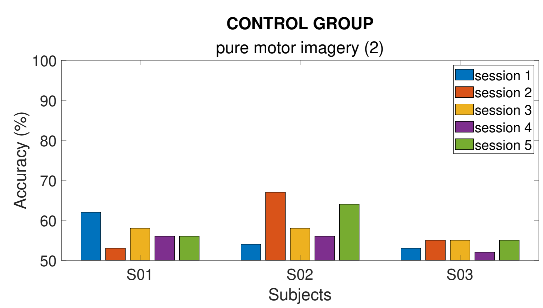

Figure 8: Mean accuracy over the sessions for the "control group" during the second part of the session of pure motor imagery.

As a whole, the improvement in classification accuracy due to the multimodal feedback should be associated with a better detection of phenomena associated with MI thanks to the proposed system. Subjects in the "neurofeedback group" actively engaged in the motor imagery task and their awareness increased. This effect has been observed despite the usage of few channels with dry electrodes and by using wearable and portable equipment. However, in some subjects, the use of dry electrodes caused discomfort towards the end of the session

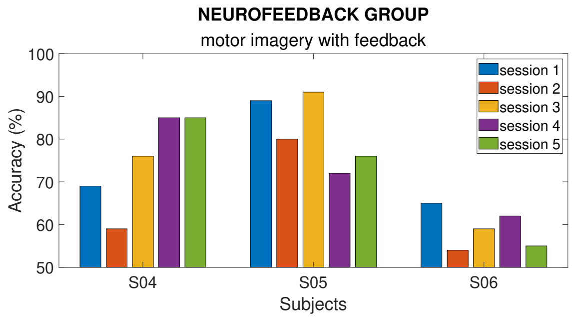

Figure 9: Mean accuracy over the sessions for the "neurofeedback group" during the online feedback.

due to the greater pressure on the scalp compared to wet electrodes. Moreover,the training effect that could be expected is not observed. As future steps, a greater experimental sample would thus be needed to make a better investigation and in-depth analyses. Metrics other than classification accuracy could be considered as well.

IV. Conclusion

An MI-based BCI has been proposed in this work and a multimodal neurofeedback has been exploited. The system was implemented with low density EEG (only eight channels), dry electrodes, a haptic suit commercialized for gaming, and a custom Unity application. A synchronous paradigm was adopted and six participants were involved in the experiments. Preliminary results show that the mean classification accuracy among subjects of the neurofeedback group is higher than the one related to the control group, thus suggesting a proper functionality of the implemented wearable and portable system. However, no training effect was observed between sessions, although this could be expected from literature. Therefore, this work will be continued by considering a greater experimental sample and deeper analyses.

V. Data availability

Part of the data used to obtain the results presented in this work can be accessed at https://metroxraine.org/contest-dataset, named "MOTOR IMAGERY DATASET".

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