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PASSIVE AND ACTIVE BRAIN-COMPUTER INTERFACES FOR REHABILITATION IN HEALTH 4.0

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Abstract – In this manuscript, the work conducted with passive and active brain-computer interfaces (BCI) within the Health 4.0 framework is reported. Such systems are feasible for a real-time personalized rehabilitation. Notably, passive BCIs are studied for detecting the engagement of patients, while active BCIs allow for an alternative mean of communication and control. Machine learning was exploited to classify the EEG signals associated with subjects' brain activity. Results show that up to 61.4% and 73.7% classification accuracy can be achieved in emotional and cognitive engagement detection respectively, while channel and training time reduction guarantees wearability of the system and less stress for the patient.

Keywords: brain-computer interface, health 4.0, wearable sensors, electroencephalography, machine learning, low-cost.

1. INTRODUCTION

Health 4.0 introduces real-time adaptivity and personalization in patient care. Moreover, healthcare services are available directly at home. Healthcare decentralization leads to several benefits: (i) cost saving, (ii) real-time feedback on patient status, and (iii) optimization of therapeutic outcome. A new interface generation guarantees unprecedented human-machine interactions. In particular, scientific and technical communities are investing heavily in brain-computer interfaces (BCI) [1]. Among biosignal-based interfaces, Brain Computer Interface allows both monitoring and control. Humans can send messages or decisions to the machines through intentional modulation of brain waves. However, through the same signal, machines acquire information on the status of the user [2]. BCIs are characterized by different paradigms, which can be usefully distinguished in passive and active [3]. In particular, in *passive paradigms* the user does not control brain activity directly and consciously and it is generally used for monitoring the user's psychophysical state. Meanwhile, in *active paradigms* the subject voluntarily modulates the brainwaves for controlling an external device without depending on external events.

Aforementioned BCI paradigms are successfully exploited in the rehabilitation field. Therapy customisation can be achieved through passive BCI. Wearability is a key factor for effective BCI use in rehabilitation, especially for active BCI. Moreover, an easy user-training improves patient's comfort. Among the neuroimaging techniques, electroencephalography (EEG) is widely employed because of portability, non-invasiveness, wearability, and cheapness [4]. Nevertheless, a cost minimization and a wearability maximization could lead to a loss of performance. A simpler hardware for signal acquisition and improved machine learning techniques for signal processing are fundamental to implement daily-life applications. In this framework, off-the-shelf instrumentation can be employed to speed up the realization of the BCI prototypes. Moreover, processing approaches have been developed and validated thanks to experimental campaigns and online available datasets.

The remainder of the paper is organized as follows. Section 2 reports the studies conducted on passive BCIs for detecting the engagement of a patient. Section 3, instead, reports the studies carried out to build a wearable system relying on motor imagery for control applications. In both sections, the technological background is revised before discussing the proposed methods, and then experimental results are reported to validate these proposal. Conclusions and future steps are addressed in Section 4.

2. PASSIVE BCI

2.1. *Background*

An interesting application of passive BCI technology is engagement detection. In 1990, William Kahn introduced the concept of engagement in the workplace [5]. Nevertheless, engagement can be also assessed in academic [6] and medical [7] fields. Engagement detection can be employed in automated or semi-automated systems to adjust their functioning to the user's current state. In the academic field, teaching strategies can be adjusted to maximize students' learning. In the medical or rehabilitation field, the adaptation of the treatment to the patient's needs leads to an optimized outcome.

Engagement can be defined by multiple dimensions: the cognitive and the emotional one. Cognitive engagement is the mental effort used to complete the task. Emotional engagement is the positive emotional reply to a task. To date, many studies do not specify the explored engagement dimensions or they focus exclusively on the cognitive one.

The aim of this study is to develop a multi-dimensional en-

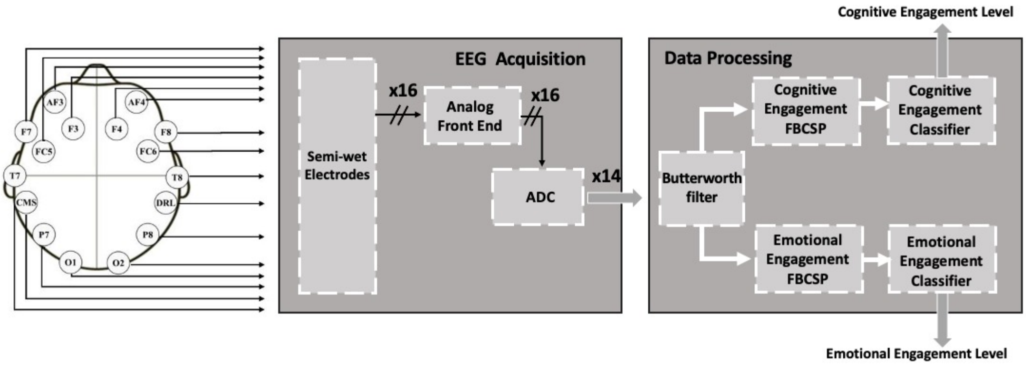

Fig. 1. Architecture Engagement detection

gagement detection system based on the simultaneous cognitive and emotional engagement assessment. The emotional engagement detection system will be presented below. A prototype, already presented in a previous study by the authors, is exploited for cognitive engagement [8]. In the following sections, the architectures for the emotional and multidimensional engagement detection systems, and the related experimental validation campaigns, are described.

2.2. *Emotional engagement detection*

The signal acquisition device proposed for the EEG-based emotional engagement detection is the *ab medica Helmate*, a wearable system equipped with 8 conductive-rubber dry electrodes. The channels are placed on: Fp1, Fp2, Fz, Cz, C3, C4, O1, and O2, according to the International 10/20 Positioning System. The EEG tracks were acquired at a sampling rate of 512 Sa/s. A [0.5- 48.5] Hz pass-band filter (zero-phase 4th-order digital Butterworth filter) was employed. The Independent Component Analysis (ICA) was applied for artifacts removal. The signal was windowed into 2 s time epochs overlapping of 1 s. The considered feature extraction algorithm involves the cascade application of a 12-bands Filter bank (FB) and the common spatial pattern (CSP): the Filter Bank decomposes the EEG signal into 12 bands (e.g. [0.5-4.5,4.5 –8.5, 8.5–12.5, ..., 44.5- 48.5] Hz) using causal Chebyshev Type II filter and the common spatial pattern (CSP) is a feature extraction algorithm used to maximize the separability between classes according to data variance.

For the classification phase, Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), Artificial Neural Networks (ANN), and k-Nearest Neighbor (k-NN) were considered. A 3-fold cross-validation was used to optimize hyperparameters. An intra-individual and an inter-individual analysis were carried out and the results were compared in terms of accuracy. Experimental validation involved twenty-five healthy Italian volunteers (52% male, 48% female, aged 38 ± 14). The standardized stimuli, proposed for eliciting emotional engagement, are images belonging to the statistically validated Oasis dataset. Each image is rated on a scale from 1.00 to 7.00 where a score equal to 1.00 corresponds to negative stimuli and 7.00 to positive ones. Subjects were shown 26 images, each for 5 s, in random order. After the projection of each image, the subject had to evaluate his/her emotional state by filling in the self-assessment manikin (SAM). The 96.2 % of accuracy with ANN in intra-individual analysis and 80.3 % with k-NN in inter-individual analysis were achieved.

2.3. *Multi-dimensional engagement detection*

Starting from the previous presented emotional engagement detection system and the cognitive engagement detection system [8], a module for engagement assessment in pediatric rehabilitation, is proposed. By combining both emotional and cognitive dimensions, four possible engagement states can be identified: (i) high engagement (positive emotional engagement and high cognitive engagement), (ii) disengagement (low cognitive engagement and negative emotional engagement), (iii) stress (high cognitive engagement and negative emotional engagement), and (iv) distraction (low cognitive engagement and positive emotional engagement). Depending on the status detected, the system provides different feedback. In case of: (i) stress, a simplification of the exercise is proposed, (ii) distraction, an element of novelty is introduced, and (iii) disengagement, a change of the activity is proposed. Such an adaptive system can be applied in automated or semi-automated rehabilitation to improve the effectiveness of the therapy.

An experimental campaign was carried out to validate the multidimensional engagement detection system in the rehabilitation field. Four children aged between five and eight years, three males and one female, suffering from neuro-motor disturbances, were involved. Due to the relevance of the frontal region for cognitive engagement detection, a different device, the 14-channel *Emotiv Epoc +*, provided with a greater number of frontal channels, is employed. EEG signals were recorded while carrying out a dynamic tracking game. By staring at a character (to choose from a bee, a ladybug, a girl, or a little fish) on the screen, the child was asked to move it.

The EEG features (obtained with the FBCSP pipeline) were input to different classifiers (K-NN, SVM and ANN) and the highest accuracy is achieved whit ANN: 61.4% and 73.7% for the emotional and cognitive engagement, respectively. The emotional engagement accuracy is lower than the already reported in the previous section. This could be due to the age and pathology of the subjects involved in the experimental campaign.

3. ACTIVE BCI

3.1. Background

In active paradigms, different types of tasks can be performed, such as mental arithmetic, motor imagery, mental counting, and music imagery. Among these, motor imagery is mostly exploited in BCI research and it is also considered in the following . Motor imagery (MI) is a cognitive process in which a subject imagines to perform a specific motor action but the movement is voluntary inhibited [9]. It was demonstrated that, during such an imagery task, the activated brain areas are compatible with the ones associated with motor execution. Despite its applicability in different fields, two major issues hinder its usability. Firstly, several EEG channels are needed to acquire enough information about the brain activity [10] and to obtain an accurate classification. Furthermore, a large amount of training data must be collected at the beginning of each MI-BCI session to tune the system for the target subject. This implies the need of an extensive training period for a new user willing to use the BCI.

In this framework, channel reduction procedures and transfer learning techniques were developed in favor of wearability and portability of the system. The former are useful to identify an optimal channels subset, which does not degrade classification performance or even improves it. The latter reduces the initial training time by using data obtained from other patients. In the next sections, the channel selection procedure is recalled from previous studies [11, 12] and it is applied in order to better highlight its effectiveness. Then, preliminary results are reported concerning a transfer learning technique with the aim to reduce the initial MI training period.

3.2. Channels reduction for multiple tasks

Minimizing the number of EEG channels is essential to develop a wearable and comfortable MI-BCI for daily-life use. In doing that, the classification performance must not be affected. The proposed technique [12] consists of a progressive selection of channels. In each iteration, the contribution of each channel to motor imagery classification was estimated, and the channel associated with optimal classification accuracy was added. Although this principle can be applied to many algorithms, the "filter bank common spatial pattern" (FBCSP) approach was chosen for features extraction and a Bayesian classifier was used. The choice is motivated by low computational burden and efficacy. In addition to the results of previous works, the method is here applied to the dataset 3a of BCI competition III. These data consist of EEG signals recorded from 3 subjects during the execution of four MI tasks: left hand, right hand, foot, and tongue. The total number of available channels is 60. In comparison, note that the previously considered dataset had only 22 available channels [12].

During the selection of a reduced channels set, the same channels are chosen for all subjects. This could imply a slight degradation in performance, but it certainly improves the inter-usability of the system. The six possible pairs of tasks have been considered for classification, as well as the four-tasks case. In the binary classifications, the accuracy goes from 75% to 93%. Though "left hand versus right hand" motor imagery may seem more intuitive, the highest classification accuracy is actually associated with the "right hand versus tongue" pair. For this particular pair, the results are shown in Fig. 2 (blue), where the mean classification accuracy among subjects and the associated standard deviation are plot as a function of the number of channels. Interestingly, just 5 channels are enough to reach an accuracy equal or greater than the 60-channels one (about 95%). For the four-tasks case, instead, the mean classification accuracy associated with all the available channels is 68.8% (Fig. 2 in red). This value can achieved with only 6 channels and it actually increases to 78.9% when 20 channels are considered. Note that, as expected, the accuracy is generally lower as the number of tasks to classify increases. These conclusions are in line with the one already discussed in [12]. Note that less channels can be considered if a small accuracy decrease is acceptable.

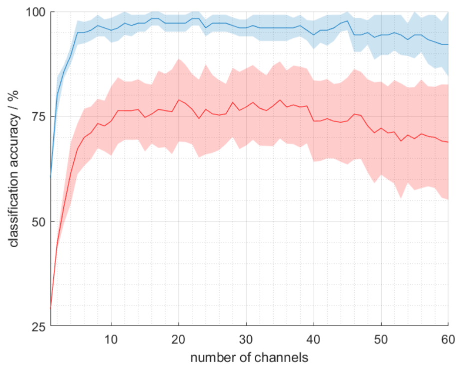

Fig. 2. Mean classification accuracy and associated standard deviation as a function of channels number: blue curve is "right hand versus tongue", red curve is the "four-tasks" case.

3.3. Reduction of training time

In a motor imagery BCI, the time required to record enough labeled data to train the algorithm is at least 20/30 minutes. Clearly, this calibration time must be reduced to avoid stress for the patient. To shorten this time, transfer learning (TL) is a possible solution. TL techniques exploit the knowledge acquired on previous data to enhance the algorithm training for the current subject. In particular, and improved CSP algorithm is here considered, namely the "composite common spatial pattern" (CCSP). For this variant of the already used FBCSP, the EEG covariance matrices associated with the brain activity spatial information are calculated by composing the covariance matrices of different subjects. The composite covariance matrix consists of a weighted sum of these matrices. The optimal weights are chosen thanks to cross-validation. Therefore, training data is exploited to find the best weights in CCSP for each patient.

The effectiveness of this approach has been validated on different datasets. Notably, the CCSP was first tested on the two benchmark datasets mentioned above, i.e. dataset 2a of BCI competition IV and dataset 3a from BCI competition III. They showed that, when simply removing 33% of data from the training set, the mean classification accuracy among the subjects drops from 80% to 73% with 15% standard deviation. Applying the CCSP, allows for a slight accuracy improvement to about 75%. Interestingly, the standard deviation associated with the mean accuracy is reduced of 5%. This implies that the performances of different subjects are more homogeneous. In addition, the technique was tested on 38 subjects of a dataset from GigaScience. On these data, the mean classification accuracy obtained with the FBCSP is 67% with 15% standard deviation. Instead, if the training data is reduced by 33%, the mean accuracy drops to 63%. In this case, thanks to the CCSP, the accuracy reaches 67.6% and the associated standard deviation is only 2.0%.

In conclusion, these preliminary results show that CCSP allows for a reduction of training time of about 33% while avoiding unacceptable decreases in accuracy or even improving it. Moreover, the performances across the subjects results more uniform.

4. CONCLUSION

This manuscript has discussed passive and active BCIs as novel tools in health 4.0. These systems allow for psychophysical state monitoring, and they provide an alternative way for communication and control. Therefore, they are well suited for a personalized rehabilitation. In such interfaces, properly measuring the brain activity is crucial. Hence, signal acquisition and processing have been treated. When building system prototypes, wearability has been stressed. More broadly speaking, user-friendliness is a key factor in addressing these systems to telemonitoring and home care services.

The discussion on passive BCI paradigms has focused on engagement detection implemented thanks to an off-the-shelf EEG cap. Meanwhile, in active BCI paradigms, reduction of EEG channels and training time has been taken into account for motor imagery detection. In both cases, machine learning techniques have been exploited to classify brain signals. The achieved results are encouraging. In engagement detection, up to 61.4% and 73.7% classification accuracies have been achieved for the emotional and cognitive engagement, respectively. In motor imagery discrimination the number of EEG channels can be reduced to about 5-9 out of 60 without accuracy degradation. Moreover, transfer learning also allows to reduce the training time of 33%. These results are a further step in the development of wearable brain-computer interfaces for a personalized rehabilitation in the health 4.0 framework.

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