Classifying human motor imagery abilities from heart rate variability analysis: a preliminary study

Classifying human motor imagery abilities from heart rate variability analysis: a preliminary study

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Abstract— **This study investigates the assessment of motor imagery (MI) ability in humans through the analysis of heartbeat dynamics. Previous studies have demonstrated that MI processes strongly influence the autonomic nervous system (ANS) activity and, consequently, this reflects on the dynamics of ANS correlates such as the Heart Rate Variability (HRV). Here, we propose to extract a set of linear and nonlinear features from the HRV signals to characterize good and bad imagers. The feature set was used as input of a pattern recognition system based on the support vector machine in order to automatically recognize good and bad imagers using only cardiovascular information. To this aim, we designed an experiment where twenty volunteers performed visual and kinaesthetic imagery tasks. Results showed an accuracy of classification between good and bad imagers over 74%.**

I. INTRODUCTION

Motor Imagery (MI) is an explicit mental simulation of actions, which allows conscious access to the neural processes involved in the planning and preparation of a movement [1]. Indeed, neuroimaging techniques have observed an overlap in the brain circuits involved in the imagination and execution of the same movement [2]. There are multiple kinds of MI. It can be experienced mentally simulating a scene in which an action is performed, i.e., making a visual representation of the action (i.e., visual imagery (VI)). Alternatively, MI can also be experienced feeling the execution of an action, i.e., based on kinaesthetic information about the movement (kinaesthetic imagery (KI)) [3].

Several studies have demonstrated many positive effects of MI in both healthy subjects and patients when it is correctly executed. Specifically, MI can improve basic motor skills and sports performance and can offer beneficial, noninvasive support to standard rehabilitation therapies [4].

However, measuring the ability to perform MI is a challenging task. To date, there are two main methods: (i) through self-administered questionnaires (Motor Imagery Questionnaire-3 (MIQ-3)and (i) calculating the mental chronometry (MC), i.e., the temporal discrepancy between the actual and the imagined motor task duration [5]. Both these methods are completely or partially based on the subjective perception of the imagination process. Indeed, although the MC grounds on the fact that executed and imagined tasks show overlapped neural patterns and similar temporal duration [6], it is calculated asking the subject to declare when the imagery process ended. As a matter of fact, none of them does actually provide an objective measure of the inter-individual physiological differences underlying MI abilities.

The aforementioned limitations have led to propose physiologically-based methods for a more objective assessment of MI ability [7]. Particularly, brain activity information has been used to measure the real engagement of an individual in an MI task as well as the goodness of the mental representation [8]. However, due to the well-known brain-heart interaction, it would be interesting to investigate possible specific patterns in the cardiovascular dynamics related to the ability to perform an MI process [9]. Indeed, during the preparation phase of action, anticipated cardio-vascular and respiratory adaptations are well-known physiological processes to face the forthcoming expenditure of energy. Moreover, the cerebral activations as well as the ventilatory and cardiovascular responses are similar during the execution and imagery of the same motor task [10], [11].

In light of this, here, we propose a pattern recognition analysis based on cardiovascular dynamics to classify two groups of subjects labeled as good and bad imagers according to their MC.

II. METHODS

A. Experimental protocol

The study was performed in accordance with the ethical standards of the Declaration of Helsinki and approved by the Bioethics Committee of the University of Pisa. Twenty volunteers (9 females; aged 25 ± 5 years), with no history of medical or neurological disorders, have been enrolled in the study.

The task consisted of pressing or imagining to press a sequence of "buttons" on a touch-screen of a tablet following a specific order. More specifically, the experiment composed of three sessions:

- MT: the subject performed the motor task by pressing each button in the right sequence.
- VI: the subject imagined himself/herself seeing his/her hand touching the screen in the right sequence.
- KI: the subject imagined to feel the same sensations he/she would feel while performing the motor task.

The two imagery tasks (i.e., VI and KI) always came after the motor one, but their order was counterbalanced randomized among participants. The duration of each task was measured by an experimenter with a chronometer. At the end of each imagery task, the performance was evaluated by computing the MC as the absolute difference between the duration of execution of the motor tasks and the duration of execution

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of the imagined tasks. After the experiment, participants have been clustered into two groups according to the MC score distribution: good imagers (MC $<$ Median$_{MC}$) and bad imagers (MC $\geq$ Median$_{MC}$). Throughout the experiment, the ECG signal was continuously using the ECG100C Electrocardiogram Amplifier from BIOPAC inc., with a sampling rate of 500 Hz. The inter-beat (RR) time series were extracted using the Pan-Tompkins algorithm. Artifact removal was processed using Kubios HRV software. Thirty-two features have been extracted from both the time and frequency domains and using nonlinear methods. Among the many nonlinear techniques, we implemented the Recurrence Quantification Analysis (RQA) to extract nonlinear information from HRV dynamics. More details on extracted feature can be found in [12], [13].

B. *Classification Analysis*

A classification analysis has been performed to automatically recognize good and bad imagers using cardiovascular features exclusively. Specifically, we implemented a support vector machine with recursive feature elimination (SVM-RFE) on the feature-vector composed of 32 features. The RFE algorithm is an example of an embedded feature selection method that follows a backward feature selection strategy. The SVM-RFE goal is to maximize the recognition accuracy and, simultaneously, explore the importance of the features related to the motor imagery process, removing irrelevant, noisy, and redundant features. To estimate the out-of-sample error, we performed a leave-one-subject-out cross-validation to mitigate the risk of a biased accuracy estimation. Particularly, we iteratively split the dataset into a training set of all the data except the samples belonging to a single remaining subject, which instead constitute the test set.

III. Results

The results of the classification analysis are shown in Figure 1. The accuracy trend is shown as a function of the number of selected features. The peak of accuracy corresponds to the subset of features that most contribute to discriminate the good vs bad imagers. The most informative features are: average of RR series ($meanRR$), average of the second derivative of the RR series ($meanDER2$), standard deviation of the second derivative of the RR series ($stdDER2$), high frequency power (HF_power), and normalized low frequency power percentage (LF_power_prc). It is worthwhile noting that these first five features achieved a maximum classification accuracy equal to 74.36%. Moreover, the class of the good imagers was recognized with 69.23%, whilst the bad imagers were recognized with 79.49%.

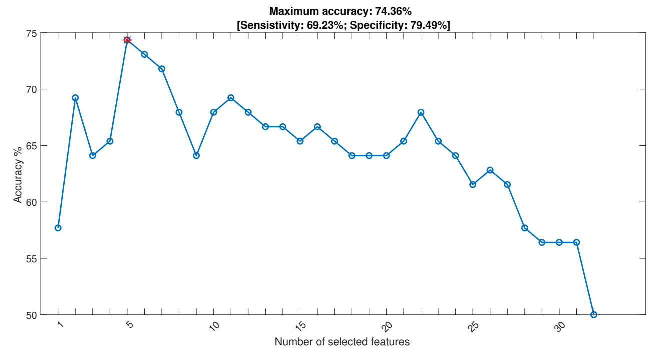

Fig. 1. Classification accuracy trend as a function of recruited features

IV. Discussion and Conclusion

In this preliminary study, we proposed a machine learning approach for the assessment of human MI ability through the analysis of heartbeat dynamics. Particularly, we studied if the mental process associated with a good or bad MI performance is also projected on the cardiovascular dynamics. We demonstrated that a specific subset of five features in time and frequency domain allows to automatically distinguish good from bad imagers with good accuracy. Moreover, it is worthwhile noting that these features contain information about both the parasympathetic activity and the modulation of cardiac autonomic outflows due to the baroreflex. These findings are in line with a previous study which indicated that only the individuals able to imagine a motor task accurately show the autonomic correlates (e.g. vagal withdrawl) of movement. Future endeavors will be directed towards the interpretation of the selected pattern and further investigation of the non-linear features.

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