Machine learning approaches for classification of imaginary movement type by MEG data for neurorehabilitation

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***Abstract*—The conducted magnetoencephalographic (MEG) experiments with voluntary participants confirm the existence of two types of motor imagery, kinesthetic imagery (KI) and visual imagery (VI), distinguished by activation and inhibition of different brain areas. Similar to real movement, KI implies muscular sensation when performing an imaginary moving action that leads to event-related desynchronization (ERD) of motor-associated brain rhythms. By contrast, VI refers to visualization of the corresponding action that results in event-related synchronization (ERS) of α- and β-wave activity. A notable difference between KI and VI groups occurs in the frontal brain area. The application of artificial neural networks allows us to classify MI in raising right and left arms with average accuracy of 70% for both KI and VI using appropriate filtration of input signals.**

Keywords—MEG analysis, motor-related patterns, machine learning algorithms, artificial neural network, motor imagery, kinesthetic imagery, visual imagery

I. INTRODUCTION

Mental imagination of movements referred to as *motor imagery* (MI) [1] manifests as a result of the rehearsal of a given motor act in the working memory without any overt movement of the corresponding muscle. It is classified into two categories: visual imagery (VI) and kinesthetic imagery (KI). While VI consists of visualization of the subject moving a limb, that does not require any special training or sensing of the muscles, KI is the feeling of muscle movement, that can usually be achieved by athletes or specially trained persons [2].

To understand and classify MI, many methods of time-frequency and spatio-temporal analyses are used. Among them, the most common techniques are using event-related synchronization (ERS) and event-related desynchronization (ERD) [3], power spectral density, wavelet transform, empirical mode decomposition, common spatial patterns, spatio-decomposition, as well as their combinations [4,5]. In addition, for classification of brain states associated with MI, the methods of machine learning and artificial intelligence are also applied to analyze EEG and MEG time series [6-8].

Although in the majority of papers devoted to MI the EEG approach was used, there was extensive research using MEG [9]. The advantages of MEG over EEG is that MEG provides a higher spatial resolution and less susceptibility to artifacts. In particular, a relatively good accuracy was achieved in classification between left-hand and right-hand MI and between MI and a rest state using the combination of a spatio-spectral decomposition and a common spatial patterns analysis [10]. Furthermore, both MEG and EEG were used in brain-computer interfaces (BCIs) for training MI classifiers [9]. The authors demonstrated rather efficient classification of MI even without separation of participants into KI and VI categories. At the same time, it was shown that KI and VI scenarios affect the classification accuracy, e.g., the accuracy rate obtained for KI were better than for VI [11]. In this context, taking into account that untrained subjects often demonstrate the VI imagery mode, the possibility to increase the accuracy rate for VI is in demand for BCI applications.

So, the goal of the present work is following: to obtain information about imagery-related brain activity for developing optimal strategies based on machine learning approaches which would provide maximal accuracy rate in classification between left-arm and right-arm MI in both groups of subjects.

II. EXPERIMENT AND METHODS

A. Design of the Experiment

The experimental study consisted of ten untrained volunteers, 8 males and 2 females between the ages of 20 and 31. The subjects were sat in a comfortable reclining chair (see Fig. 1). All participants were required to imagine moving their arms after being presented with audible beeps. The design of the experiment is shown in Fig. 1. The beeps were presented with time gaps randomly varied from 6 to 8 seconds. The number of trials per limb was varied among the subjects from 16 to 28. We provided a 20-s gap after finishing all trials for each arm and a resting 60-s interval between each series.

The neurophysiological data were acquired with the Vectorview MEG system (Elekta AB, Stockholm, Sweden) with 306 channels (102 magnetometers and 204 planar gradiometers) placed inside a magnetically shielded room (Vacuum Schmelze GmbH, Hanau, Germany) at the Laboratory of Cognitive and Computational Neuroscience, Center for Biomedical Technology, Technical University of Madrid, Spain.

Artifacts in the MEG recordings were removed using the temporal signal-space separation method of Taulu and Hari [12]. Once the events were marked at the beginning of each limb movement imagination, we extracted the 5-s trials just after these marks. Similarly, the 20-s trials corresponding to the resting state with closed eyes were also marked as the background activity of each subject.

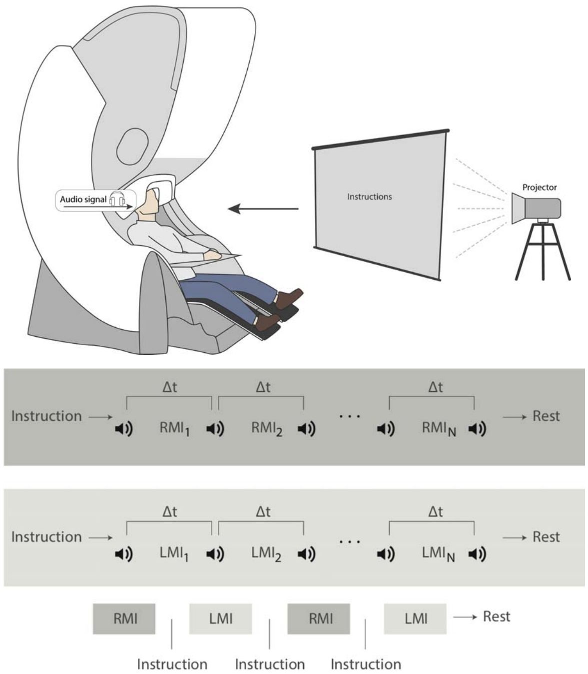

Fig. 1. Design of the MEG experiment on motor imagery. Schematic representation of experimental performance and design of the experiment. RMI$_i$_ and LMI$_i$ are time intervals corresponding to right-arm and left-arm MI, respectively.

B. *Artificial Neural Network Application*

For classification of the brain states associated with MI, we used the artificial neural network (ANNs) called multilayer perceptron (MLP). Previously, the MLP architecture was effectively used in the MEG study for detection of human decision-making uncertainty [13] and the EEG analysis of bistable image interpretations [6].

We constructed the MLP which consisted of an input layer with selected number of MEG channels for training/testing the network, followed by three hidden layers with 30, 15 and 5 neurons, respectively. The output layer comprises of a single neuron. We taught the MLP to classify the brain states of the neural ensemble through optimization of the weights of links and displacements by means of minimization of the root mean square error. We used the training algorithm called scaled conjugate gradient.

The input data were filtered by a low-pass filter of order 70 with a cutoff frequency F_c changing according to each study. Mixing the input data usually improves the efficiency of the machine learning algorithm. In this work, we used a random mixing of the input signals corresponding to a particular task. First, we trained the ANN using 75% of MEG trials and then tested it with the resting 25% trials. The ANN classification was carried out in MATLAB using the Neural Network Toolbox. We applied MLP to classify MEG time series trials associated with left-arm and right-arm MI.

III. Results

Figure 2 illustrates the variation of the maximal ANN accuracy (in %) in differentiation between MI of the left and right arms versus the cutoff frequency F_c of the low-pass filter for KI (squares) and VI (triangles) subjects. In Fig. 2a all 102 magnetometers were used for the analysis, while in Fig. 2b we only used 13 most informative channels localized near the left-parietal cortex. One can see that in the latter case the maximal classification accuracy almost does not change as compared with the case of using all 102 channels, and for some subjects (subjects 8 and 10) reaches 78%. However, the best accuracy is achieved by using all channels; it reaches 90% for subject 6. In both cases, the average classification accuracy over all subjects is about 70%. The obtained results demonstrate that high classification accuracy can be achieved for all subjects, regardless of which group they belong to, by the appropriate selection of the cutoff frequency of the low-pass filter.

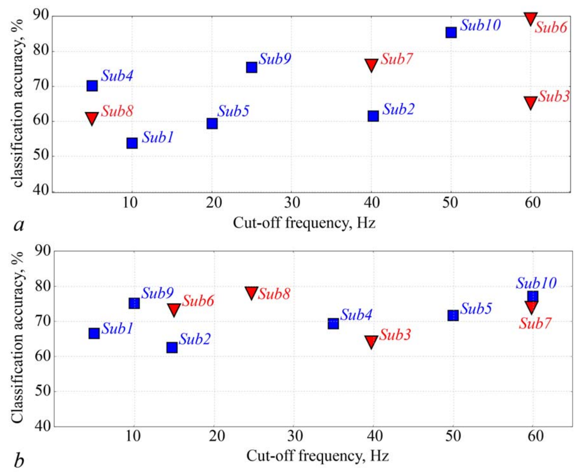

Fig. 2. ANN classification accuracy of MI of left and right arms versus cut-off frequency for KI (squares) and VI (triangles) subjects, obtained using (a) 102 and (b) 13 channels. Each data point indicates the maximal value of the classification accuracy for every subject and the corresponding cutoff frequency F_c, at which this maximal accuracy is achieved.

It should be noted that the results presented in Fig. 2 are closely related to the ANN optimization problem, important for classification of motor-related signals of electrical brain activity [7, 14-18]. It is known that including all possible features of a multichannel neurophysiological data, e.g., EEG or, more significantly, MEG, results in an extremely large phase-space dimension, that has to be analyzed by the classifier. On one hand, this is a critical issue for BCI, where all calculations should be performed in real time by portable computers and the calculation performance is of extreme importance [14-18].

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