Kinesthetic and visual modes of imaginary movement: MEG studies for BCI development

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***Abstract*— The study of neurophysiological mechanisms responsible for motor imagery is important for the development of brain-computer interfaces (BCI). Here we analyze the results of magnetoencephalographic (MEG) experiments which confirm the existence of two types of motor imagery, kinesthetic and visual imagery, distinguished by activation and inhibition of different brain areas in motor-related alpha (8-12 Hz) and beta (15-30 HZ) frequency ranges. Kinesthetic imagery implies muscular sensation when performing an imaginary moving action that leads to event-related desynchronization (ERD) of motor-associated brain rhythms. By contrast, visual imagery refers to visualization of the corresponding action that results in event-related synchronization (ERS) of alpha/beta activity. A main difference between kinesthetic and visual modes occurs in the frontal brain area. The analysis of evoked responses shows that in all kinesthetic imagery subjects the activity in the frontal cortex is suppressed during motor imagery, while in the visual imagery subjects the frontal cortex is always active. The accuracy in classification of left- and right-arm motor imagery using artificial intelligence methods is similar for kinesthetic and visual imagery modes. The possibility to increase the accuracy for visual imagery is in demand for BCIs.**

Keywords—brain-computer interface, motor imagery, bioprosthetics, MEG, machine learning

I. Introduction

The revealing features of brain activity during imagination of the movement of different limbs are very important for fundamental neuroscience and applied neurotechnologies, such as BCIs which can help in rehabilitation of patients after trauma or stroke, as well as for noninvasive brain-controlled bioprostheses and exoskeletons [1]. Mental imagination of movements referred to as motor imagery [2] 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, namely, visual and kinesthetic imagery [3]. While visual imagery consists of visualization of the subject moving a limb, that does not require any special training or sensing of the muscles, kinesthetic imagery is the feeling of muscle movement, that can usually be achieved by athletes or specially trained persons [4].

To understand and classify motor imagery different methods of time-frequency analyses are used, in particular, the most common techniques are using ERS and ERD, wavelet transform, empirical mode decomposition, common spatial patterns, as well as their combinations [5-8]. Due to good spatial and frequency resolution MEG was extensive used for motor imagery studies [9]. However, to the best of our knowledge, the MEG experiments with untrained subjects were not carried out for classification of different modes of imaginary movement.

Early, it was shown that kinesthetic and visual imagery modes affect the classification accuracy, e.g., the accuracy rate obtained for kinesthetic imagery were better than for visual one [10]. In this context, taking into account that untrained subjects often demonstrate the visual imagery mode, the possibility to increase the accuracy rate for visual imagery is in demand for BCI applications.

II. Experiments and Metods

The experimental study consisted of ten untrained volunteers. The subjects were sat in a comfortable reclining chair with their legs straight and arms resting on an armrest in front of them. All participants were required to imagine moving their arms after being presented with audible beeps as the cue. The whole MEG experiment was divided into four series with one-fourth of the total number of trials in each series. Each series consisted of equal number of trials randomly chosen for each of two arms (left or right arm). The imaginary movement of each arm was counted as one trial. The beeps were presented with time gaps randomly varied from 6 to 8 s. The number of trials per limb was varied among the subjects from 16 to 28. All participants provided a written informed consent before the experiment commencement. The experimental studies were performed in accordance with the Declaration of Helsinki. Methods were carried out in accordance with approved guidelines. The neurophysiological data were acquired with the Vectorview MEG system (Elekta AB, Sweden) with 102 magnetometers placed inside a magnetically shielded room at the Laboratory of Cognitive and Computational Neuroscience, Center for Biomedical Technology, Technical University of Madrid, Spain. The research was approved by the Ethics Committee of the Technical University of Madrid.

The time-frequency spectrogram (TFS) of the MEG signals was analyzed using wavelet-based approach, a well-known tool for the analysis of non-stationary time series [6,7]. For each limb, we used the Morlet wavelet to evaluate the TFS for all extracted epochs, and then averaged the TFSs for the limb. Then, the TFS was also averaged over the desired motor-related frequency ranges of alpha (8–12 Hz) and beta (15–30 Hz) bands. The same process was repeated over the resting state using the same parameters. To evaluate ERS/ERD, we took the difference between the spectrogram for the trials and the averaged-over-time spectrogram of the resting state and then normalized it to the resting state [11].

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To classify MEG trials we have used two different machine learning technics. First, to perform the cluster analysis of kinesthetic and visual imagery, we applies the hierarchical cluster analysis (HCA) [12], a widely-used unsupervised machine learning technique. Using the HCA, we found the hierarchy in considered data in a greedy way, that allowed to uncover its structural properties, i.e., organize observed objects into subgroups. Second, to classify the brain states associated with motor imagery, we used such type of artificial neural network as multilayer perceptron (MLP) [13] which is often used for classification of EEG trials [14,15].

III. Results

We analyzed brain dynamics in terms of ERS/ERD in alpha (8–12 Hz) and beta (15–30 Hz) frequency bands during the motor imagery performance, which allowed us to classify the subjects into kinesthetic and visual categories. We shown that the kinesthetic imagery subjects have stronger ERD centralized near the inferior-parietal lobe, while the visual imagery subjects tend to have ERS in the superior-parietal and occipital lobes.

The obtained results of classification into kinesthetic and visual imagery groups was confirmed by the analysis of the evoked response, which is the average of time series over all trials. The subjects from the visual imagery group are characterized by neural activation of the occipital cortex in contrast to the subjects from the kinesthetic imagery group, who demonstrate activity in the premotor area, which is absent in the visual imagery group.

The HCA results are present in Fig 1, where the dendrogram with the arrangement of clusters obtained by HCA is shown. One can see that all subjects can be well separated into two large clusters with the exception of the upper row of the dendrogram marked by the dashed lines, i.e., subjects 3, 4, 5, 6, 7 and 8 are arranged into the kinesthetic imagery group, while the rest of the subjects 1, 2, 9 and 10 are arranged into the VI group. It should be noted, that the links between the subjects inside each group are much smaller than the links between the clusters. This confirms that HCA provides a good enough precision for the clustering.

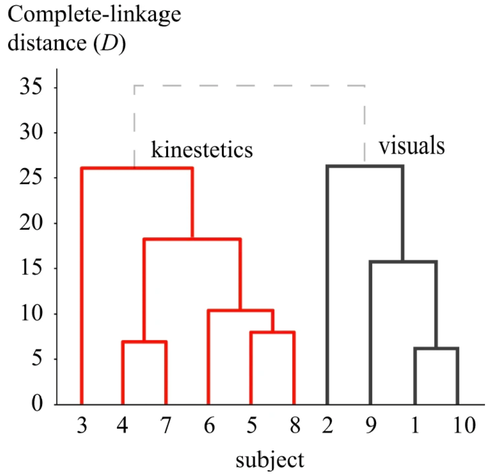

Fig. 1. Results of HCA illustrating the clustering of subjects belonging to kinesthetic and visual imagery types. Here dendrogram shows the formation of two subgroups (kinesthetic and visual imagery subjects) in terms of Euclidean distance between clusters in ERD/ERS feature space.

The brain activity during motor imagery of the kinesthetic subjects is characterized by well-pronounced ERD in both alpha and beta frequency bands. Such a behavior is similar to real movement when alpha- and beta-wave energies are suppressed in the motor brain area [16]. On the contrary, for the visual imagery subjects the motor imagery process is accompanied by ERS in the alpha and beta ranges, that determines a leading role of self-visualization of the limb movement.

A multilayer perceptron was constructed and applied to classify MEG time series trials associated with left-arm and right-arm motor imaginery in these two groups of subjects. Fig. 2 demonstrates the classification accuracy for each subject. The average classification accuracy over all subjects was about 70%. At the same time, the best accuracy reached 90% for subject 6.

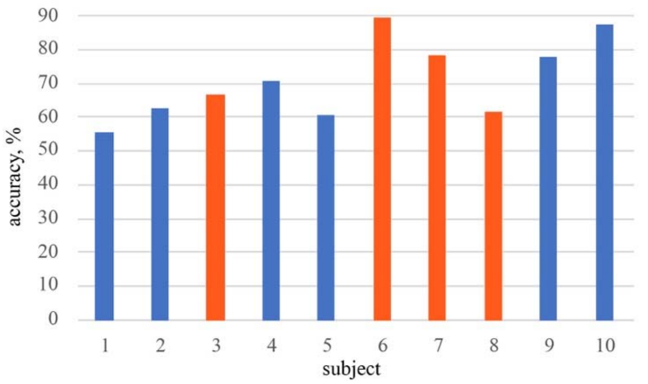

Fig. 2. Results of ANN classification accuracy of motor imagery of left and righ arm. Orange boxes correspond to visual imaginery subjects, blue boxes – kinesthetic imaginery subjects.

This is an important result, which shows that the classification accuracy does not depend on the type of imagination. We can get high classification accuracy for both kinesthetic and visual types of imagination. This opens up opportunities for improving the efficiency of the active interfaces of the brain-computer, which exploit imaginary movements as mental commands.

IV. Conclusion

We analyze the results of MEG experiments with voluntary participants which confirm the existence of two types of motor imagery, kinesthetic and visual imagery, distinguished by activation and inhibition of different brain areas in motor-related alpha and beta frequency ranges. Similar to real movement, kinesthetic imagery implies muscular sensation when performing an imaginary moving action that leads to ERD of motor-associated brain rhythms. By contrast, visual imagery refers to visualization of the corresponding action that results in ERS of alpha and beta activity. A notable difference between kinesthetic and visual modes of imagination occurs in the frontal brain area. The analysis of evoked responses shows that in all kinesthetic imagery subjects the activity in the frontal cortex is suppressed during motor imagery, while in the visual imagery subjects the frontal cortex is always active. The accuracy in classification of left-arm and right-arm motor imagery using maschine learning is similar for kinesthetic and visual imagery modes. Since untrained subjects usually demonstrate the visual imagery mode, the possibility to increase the accuracy for visual imagery is in demand for BCIs.

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