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Using artificial neural networks for classification of kinesthetic and visual imaginary movements by MEG data

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ABSTRACT

The analysis of neurophysiological mechanisms responsible for motor imagery is essential for the development of brain-computer interfaces. The carried out 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. For classification of the brain states associated with motor imagery, we used the hierarchical cluster analysis and a popular type of artificial neural networks called multilayer perceptron. The application of machine learning techniques allows us to classify motor imagery in raising right and left arms with an average accuracy of 70% for both KI and VI using appropriate filtration of input signals. The same average accuracy is achieved by optimizing MEG channels and reducing their number to only 13.

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

1. INTRODUCTION

Mental imagination of movements referred to as motor imagery (MI)[1] manifests as a result of the repetition 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 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.[4–10] 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.[11–15]

Although in the majority of papers devoted to MI the EEG approach was used, there was extensive research using MEG.[16] 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.[17] Furthermore, both MEG and EEG were used in brain-computer interfaces (BCIs) for training MI classifiers.[16] 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.[18] 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.[19–21]

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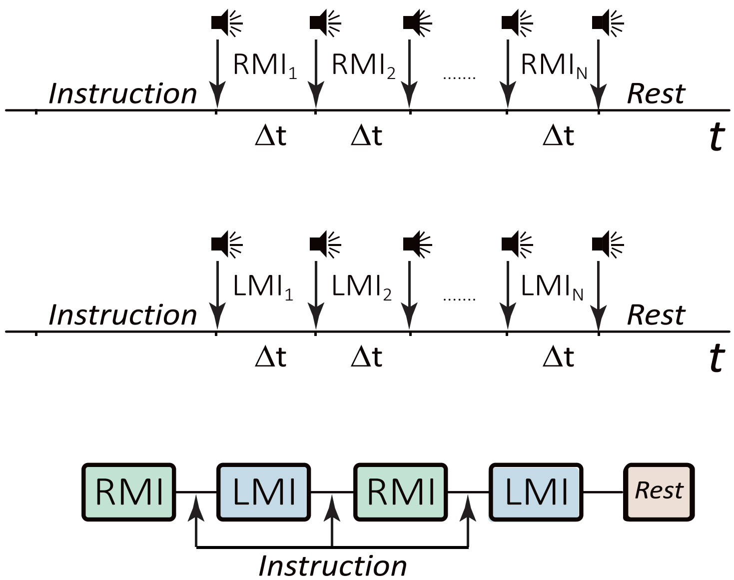

Figure 1. Design of the MEG experiment on motor imagery. Schematic representation of experimental performance and design of the experiment. RMI_i and LMI_i are time intervals corresponding to right-arm and left-arm MI, respectively

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.

2. 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.[22] 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.

3. MACHINE LEARNING TECHNIQUES

For classification of the brain states associated with MI, we used two different machine learning techniques. To perform the cluster analysis of kinesthetic and visual imagery, we have applied the hierarchical cluster analysis (HCA)[23] — a widely-used unsupervised machine learning technique. Using the HCA, we have found the hierarchy in considered data that allowed to uncover its structural properties and to organize observed objects into subgroups.

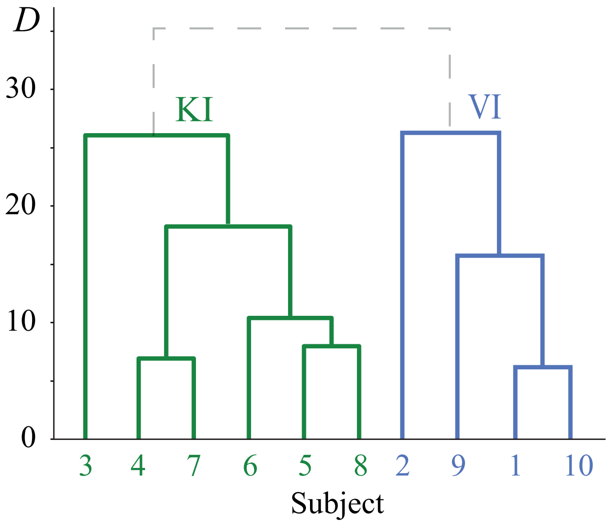

Figure 2. Results of HCA illustrating the clustering of subjects belonging to kinesthetic and visual imagery types. Here dendrogram shows the formation of two subgroups (kinesthetic and visual imagery subjects) in terms of Euclidean distance between clusters in ERD/ERS feature space (complete-linkage distance D).

To classify the brain states associated with motor imagery, we have used the artificial neural network (ANN) called multilayer perceptron (MLP)[24] which is often used for classification of EEG trials.[11,13,25] Previously, the MLP architecture was effectively used in the MEG study for detection of human decision-making uncertainty[26] and the EEG analysis of bistable image interpretations.[4]

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.

4. 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 have 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 were 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 presented in Fig. 2 where the dendrogram with the arrangement of clusters obtained by the 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.

Subject	**MI Type**	F_c**, Hz**	**Accuracy, %**
1	KI	10	53
2	KI	40	61
4	KI	5	70
5	KI	20	60
9	KI	25	77
10	KI	50	86
3	VI	60	66
6	VI	60	90
7	VI	40	77
8	VI	5	60

Table 1. The maximal values of the classification accuracy for every subject and the corresponding cutoff frequency values F_c when using 102 MEG channels.

A multilayer perceptron was constructed and applied to classify MEG time series trials associated with left-arm and right-arm motor imaginery in KI and VI groups of subjects. Tables 1 and 2 show the maximal values of MLP accuracy (in percents) in differentiation between MI of the left and right arms and the corresponding cutoff frequency values F_c of the low-pass filter for KI and VI subjects. In Table 1 all 102 magnetometers were used for the analysis, while in Table 2 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.

Subject	**MI Type**	F_c**, Hz**	**Accuracy, %**
1	KI	5	67
2	KI	15	63
4	KI	35	70
5	KI	50	71
9	KI	10	75
10	KI	60	78
3	VI	40	65
6	VI	15	73
7	VI	60	74
8	VI	25	78

Table 2. The maximal values of the classification accuracy for every subject and the corresponding cutoff frequency values F_c when using 13 MEG channels.

It should be noted that the presented results are closely related to the ANN optimization problem, important for classification of motor-related signals of electrical brain activity.[13,27,28] 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.[29]

5. DISCUSSION AND CONCLUSION

Based on the analysis of the results of MEG experiments we have confirmed 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 MLP 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.

6. ACKNOWLEDGMENTS

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