Analysis of the features of brain neuronal sources during imagery motor activity: MEG study

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***Abstract*—We analyzed the features of motor imagery (imagery arms movements) in the source level, applying the Dynamic Imaging of Coherent Sources method to MEG signals. We obtained the results that have confirmed the existence of two types of motor imagery: visual imagery and kinesthetic imagery. We have analyzed averaged distributions of normalized sources power for the visual imagery and kinesthetic imagery subgroups of volunteers and identified the main differences between these types of motor imagery in terms of the excitation of sources of neural activity.**

***Index Terms*—MEG analysis, source localization, beamformer technique, dynamic imaging of coherent sources, imagery motor activity, brain-computer interface**

I. Introduction

Magnetoencephalography (MEG) and electroencephalography (EEG) are very popular and effective noninvasive neuroimaging techniques [1]–[14]. However, these methods do not provide access to the sources of neural activity, but represent, in fact, an instant linear superposition of the activity of several sources [15]–[21]. In other words, the same activity area in the brain is usually registered by several adjacent sensors at once (the so-called “field spread” problem), which complicates the correct interpretation of the obtained signals. This problem can be solved quite effectively by analyzing neural interactions in the space of sources of oscillatory activity in the brain, the characteristics of which (position and power) can be reconstructed, using special methods — based on the solution of the so-called inverse problem [15], [22]. Another significant reason for the transition to the source space is the ability to determine the actual anatomical location of the interacting areas of the brain.

In work [1], MEG studies of the features of event-related fields during the execution of imagery movements were carried out at the sensor level. This work confirmed the existence of two types of motor imagery (kinesthetic imagery (KI) and visual imagery (VI)) and revealed the differences between them in terms of characteristics of the event-related fields. Namely, KI implies muscular sensation when performing an imaginary moving action leading to event-related desynchronization (ERD) of motor-associated brain rhythms. On the contrary, VI refers to the visualization of the corresponding action that results in event-related synchronization (ERS) of α- and β-wave activity. Nevertheless, the analysis of differences at the source level during the execution of different types of imagery movements remains a poorly studied issue here.

The goal of the present work is to identify by MEG data the features of each type of motion at the source level.

II. Design of the Experiment

Brain magnetic fields were recorded in a magnetically shielded room with a whole-head Vectorview MEG system (Elekta AB, Stockholm, Sweden) with 306 channels (102 magnetometers and 204 planar gradiometers) at the Laboratory of Cognitive and Computational Neuroscience, Center for Biomedical Technology, Technical University of Madrid, Spain. The sampling frequency was 1000 Hz and an online anti-alias bandpass filter between 0.1 and 330 Hz was utilized.

Ten healthy untrained volunteers participated in the experimental study. All subjects provided a written informed consent before the commencement of the experiment. The experimental studies were performed in accordance with the Declaration of Helsinki. The volunteers were sat in a comfortable reclining

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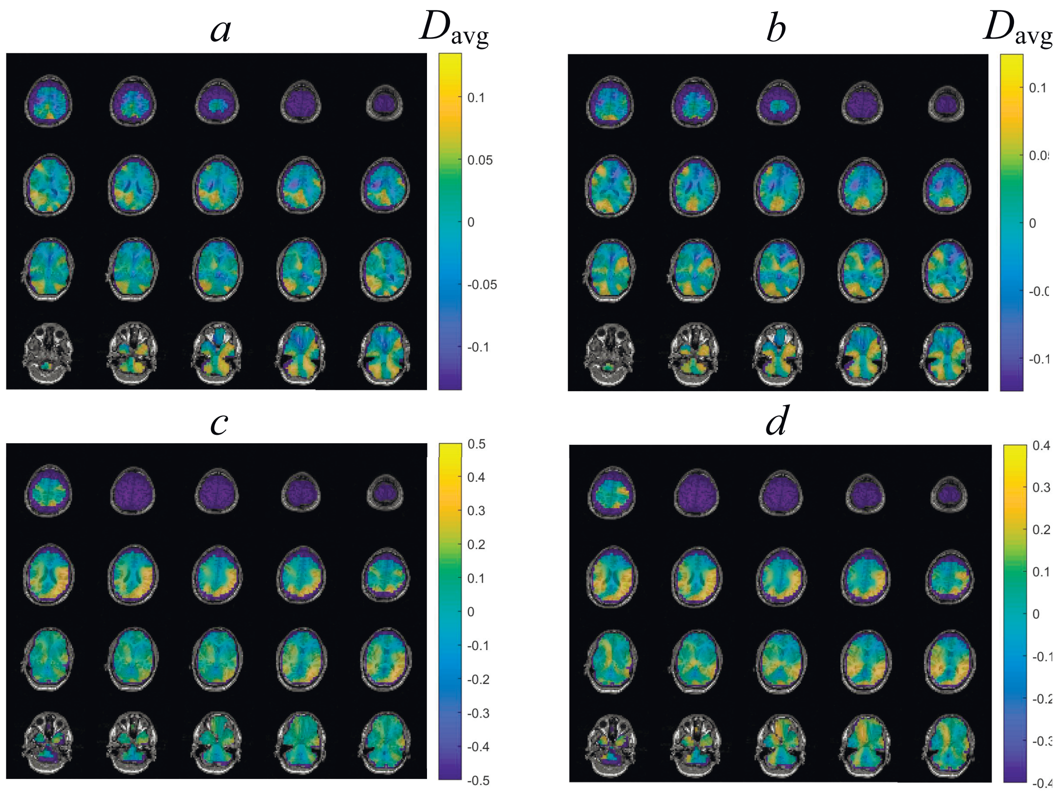

Fig. 1. Distributions of normalized sources power D_{avg} averaged over the subgroup of volunteers (4 subjects) characterized by VI (*a* and *b*) and over the subgroup of volunteers (6 subjects) characterized by KI (*c* and *d*) plotted superimposed on the anatomical MRI in slice mode for left arm imagery movements (*a* and *c*) and right arm imagery movements (*b* and *d*). Frequencies of interest: 11 ± 2 Hz.

chair with their legs straight and arms resting on an armrest in front of them. All participants were required to imagine moving their arms (left or right) after being presented with audible beeps as the cue.

The experiment was divided into 4 series, and each series consisted of equal number of trials randomly chosen for each of two arms (left or right arm motor imagery). Before changing the arm, the subject was informed on the screen about which arm he must imagine to move after the beep. The imaginary movement of each arm was counted as one trial. The beeps were presented with time gaps randomly varied from 6 to 8 seconds. A 20-s gap after finishing all trials for each arm and a resting 60-s interval between each series was provided.

III. Methods

Artifacts in the MEG recordings were removed using the temporal signal-space separation method of Taulu and Hari [23]. Once the events were marked at the beginning of each limb movement imagination, we extracted the 5-s trials just after these marks and redefined then the length of every trial as [1 s, 5 s] to reduce the effect of a transient process. As a result, we obtained at least 24 event-related trials for each arm of each volunteer. The 20-s trials corresponding to the resting state with closed eyes were also marked as the background activity of each subject. All further operations were performed using the Fieldtrip toolbox [24].

We applied a beamformer technique in the frequency domain — Dynamic Imaging of Coherent Sources (DICS) — allowing us to estimate the strength of oscillatory activity at any given location in the brain [24], [25]. As the forward model, we used here a semi-realistic head model developed by Nolte [26]. To construct it, we used "Colin27" head averaged template MRI [27] available in FieldTrip and the data of the subject head shape recorded by Polhemus before the beginning of the MEG experiment. The head volume was discretized with respect to a grid with 0.7 cm resolution, and the source power for each of 9025 grid points was computed. The frequency of interest was 11 Hz and the smoothing window was +/-2 Hz (α-rhythm).

Note, we performed reconstruction of the activity of the sources separately for all the 4-second trials, using the described above DICS method with the prepared forward model and the aligned head model. As a result, for every trial, we obtained the power distribution of the activity of the sources in the brain on the 3D grid with 9025 voxels: P_i – for the i-th event-related trial and PB_i – for the i-th background trial. Then we calculated the normalized difference of the sources power distributions (the so-called baseline correction): $D_i = (P_i – PB_i)/PB_i$. This procedure is necessary to isolate the event-related pattern of sources activity. Finally, we averaged the resulting normalized sources power distributions and obtained one distribution for the given volunteer — D. This distribution was then overlaid on the template MRI scan.

The above operations were performed for each volunteer, and distributions of normalized sources power averaged over volunteers were calculated.

IV. Results and Discussion

The obtained results have confirmed in the source level the existence of two types of MI: part of the volunteers demonstrate VI, and the rest — KI. Fig. 1 shows the distributions of normalized sources power averaged over the VI and KI subgroups of volunteers. One can see that in α-band visual imagery is characterized by predominant activation of the occipital brain region (the visual cortex responsible for processing visual stimuli and imagination), while kinesthetic imagery is characterized by the increasing activity of the motor cortex. We emphasize that Fig. 1 shows the power distributions averaged over all subjects, therefore each subject is characterized by a different degree of expression of KI or VI. We also note that the feature of contralaterality is pronounced only for the KI by the right hand (see Fig. 1c).

V. Conclusion

Using the Dynamic Imaging of Coherent Sources method and MEG data, we obtained the results in the source level that have confirmed the existence of two types of motor imagery: visual imagery and kinesthetic imagery. We have analyzed averaged distributions of normalized sources power for the VI and KI subgroups of volunteers and identified the main differences between these types of motor imagery in terms of the excitation of sources of neural activity. The feature of contralaterality is pronounced only for the KI by the right hand.

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