Peculiarities of brain activity sources in the process of motor acts imagination

Kurkin, Semen, Chholak, Parth

Semen Kurkin, Parth Chholak, "Peculiarities of brain activity sources in the process of motor acts imagination," Proc. SPIE 11847, Saratov Fall Meeting 2020: Computations and Data Analysis: from Molecular Processes to Brain Functions, 118470T (4 May 2021); doi: 10.1117/12.2591371

SPIE.

Event: Saratov Fall Meeting 2020, 2020, Saratov, Russian Federation

Peculiarities of brain activity sources in the process of motor acts imagination

Semen Kurkin[a], Parth Chholak[b]

[a]Neuroscience and Cognitive Technology Lab,
Center for technologies in robotics and mechatronics components,
Innopolis University, 1, Universitetskaya Str., Innopolis, 420500, Russia;
[b] Center for Biomedical Technology Technical University of Madrid, Spain

ABSTRACT

The analysis of neurophysiological mechanisms responsible for the imagination of movements is essential for developing brain-computer interfaces. We have carried out MEG experiments with voluntary participants performing imaginary movements. We have analyzed the features of motor imagery (imagery arms and legs movements) at the source level. We have obtained the results that confirmed 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. We have applied statistical cluster-based permutation test to identify the differences between the averaged distributions of normalized sources power for visual and kinesthetic imagery.

Keywords: MEG analysis, source localization, beamformer technique, dynamic imaging of coherent sources, imagery motor activity, cluster-based permutation test, brain-computer interface

1. INTRODUCTION

Magnetoencephalography (MEG) and electroencephalography (EEG) are very popular and effective noninvasive neuroimaging techniques.[1–12] However, these methods do not provide access to the sources of neural activity but represent an instant linear superposition of the activity of several sources.[13–20] 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 oscillatory activity sources in the brain. The characteristics of sources (positions and power) can be reconstructed using special methods based on the solution of the so-called inverse problem.[13,21] Another significant reason for the transition to the source space is determining the actual anatomical location of the interacting areas of the brain.

Mental imagination of movements referred to as motor imagery (MI)[22] manifests as a result of the repetition of a given motor act in the working memory without any corresponding muscle movement. 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 sense of the muscles, KI is the feeling of muscle movement that can usually be achieved by specially trained persons.[23] To understand and classify MI, one can use methods of time-frequency and spatio-temporal analyses. The most common techniques use event-related synchronization (ERS) and event-related desynchronization (ERD),[24] power spectral density, wavelet transform, empirical mode decomposition, common spatial patterns, spatio-decomposition, as well as their combinations.[5,14,25–27] Also, for the classification of brain states associated with MI, machine learning and artificial intelligence methods are applied to analyze EEG and MEG time series.[2,8,9,11,28]

In works,[1,19] 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

Further author information: (Send correspondence to S.A. Kurkin)
S.A. Kurkin: E-mail: kurkinsa@gmail.com, Telephone: +7 9270 55 77 70

Saratov Fall Meeting 2020: Computations and Data Analysis: from Molecular Processes to Brain Functions, edited by Dmitry E. Postnov, Proc. of SPIE Vol. 11847, 118470T

· doi: 10.1117/12.2591371

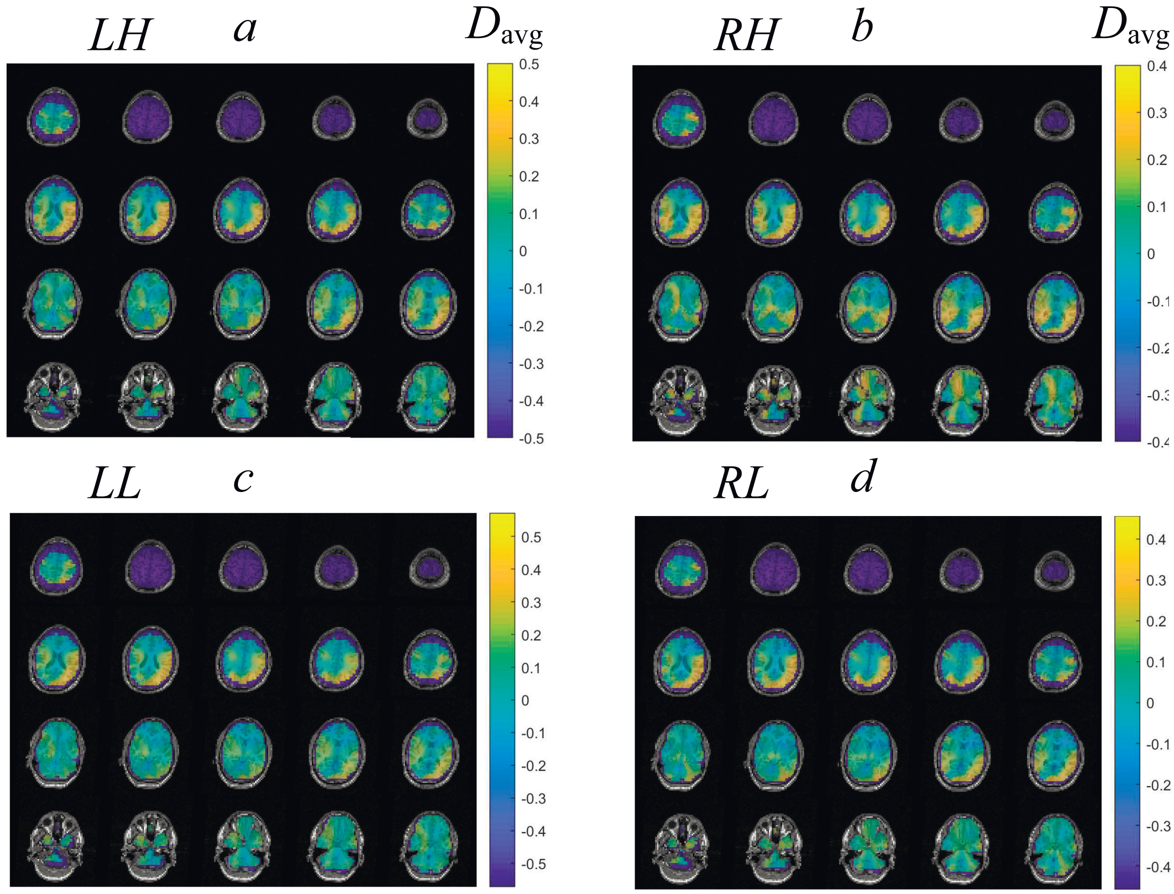

Figure 1. Distributions of normalized sources power D_{avg} averaged over the subgroup of volunteers (6 subjects) characterized by kinesthetic imagery plotted superimposed on the anatomical template MRI in slice mode for left and right arms imagery movements (a and b) and left and right legs imagery movements (c and d). Frequencies of interest: 11 ± 2 Hz. The following abbreviations are used: LH – left hand, RH – right hand, LL – left leg, RL – right leg.

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 investigate the features of each type of motion at the source level by MEG data.

2. 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 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.

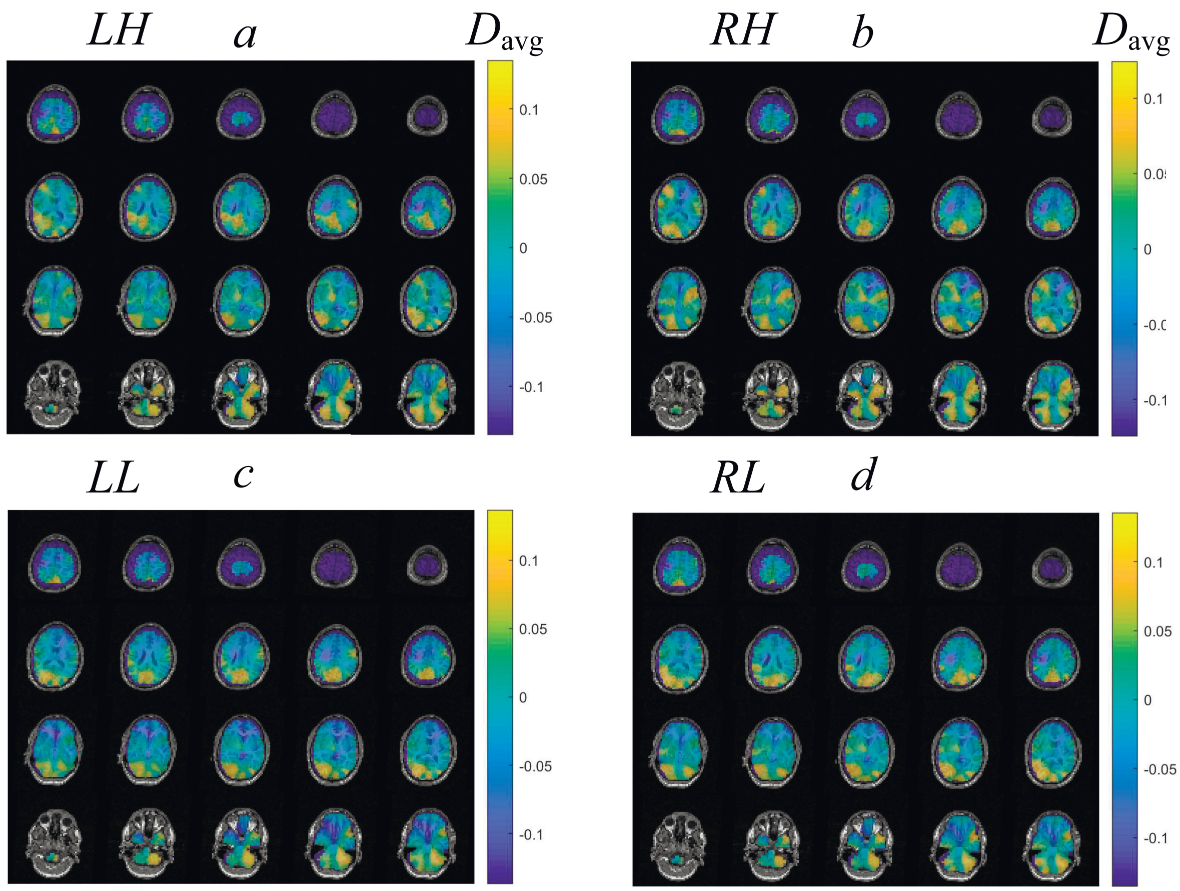

Figure 2. Distributions of normalized sources power D_{avg} averaged over the subgroup of volunteers (4 subjects) characterized by visual imagery plotted superimposed on the anatomical template MRI in slice mode for left and right arms imagery movements (a and b) and left and right legs imagery movements (c and d). Frequencies of interest: $11 \pm 2\,\mathrm{Hz}$. The following abbreviations are used: LH – left hand, RH – right hand, LL – left leg, RL – right leg.

Ten healthy untrained volunteers participated in the experimental study (8 males and 2 females between 20 and 31 years old). All subjects provided written informed consent before the commencement of the experiment. The experimental studies were performed in accordance with the Declaration of Helsinki. Volunteers 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/legs (left or right) after being presented with audible beeps as the cue.

The experiment was divided into four series. Each series consisted of an equal number of trials randomly chosen for each of the limbs (left or right arm/leg motor imagery). Before changing the arm/leg, the subject was informed on the screen about the type of subsequent task. The imaginary movement of each limb 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 limb and a resting 60-s interval between each series was provided.

3. METHODS

We removed artifacts in the MEG recordings, using the temporal signal-space separation method of Taulu and Hari.[29] Once the events were marked at the beginning of each limb movement imagination, we extracted the

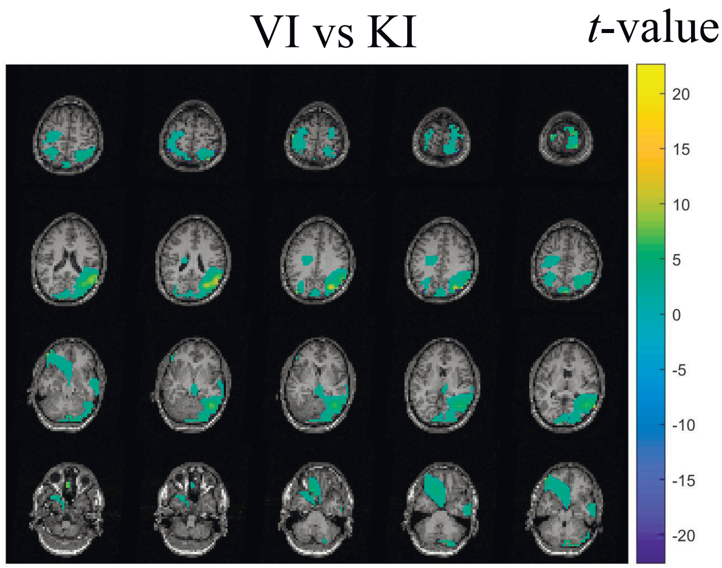

Figure 3. Clusters in the source space plotted superimposed on the anatomical template MRI in slice mode. The color scale represents t-value as the result of the comparison between VI (any movement) and KI (any movement); $p_{pairwise} < 0.05$, $p_{cluster} < 0.025$.

5-s trials just after these marks. Then, we redefined 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 limb 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. We performed all further operations using the Fieldtrip toolbox.[30]

We applied Dynamic Imaging of Coherent Sources (DICS), a beamformer technique in the frequency domain, allowing one to estimate the strength of oscillatory activity at any given location in the brain.[30,31] As the forward model, we used a semi-realistic head model developed by Nolte.[32] To construct it, we used "Colin27" head averaged template MRI[33] available in FieldTrip, and the data of the subject head shape recorded by Polhemus before the beginning of the MEG experiment. Head volume was discretized on a grid with 0.7 cm resolution, and the source power for each of the 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 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 (performed 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 also calculated.

We conducted a statistical cluster-based permutation test on the obtained sets to determine significant differences between power distributions corresponding to the two given conditions.[34,35] To match the discovered significant clusters in the difference of the power distributions with the brain's anatomical regions, we used the Automated Anatomical Labeling (AAL) brain atlas.[36]

4. RESULTS AND DISCUSSION

The obtained results have confirmed the existence of two types of motor imagery in the source level. Indeed, part of the volunteers demonstrates visual imagery, and the rest — kinesthetic imagery. Fig. 1 shows the distributions of normalized sources power averaged over the KI subgroup of volunteers for left/right arms/legs imagery movements. Fig. 2 demonstrates the similar distributions for the VI subgroup. One can see that visual imagery is characterized by predominant activation of the occipital brain region in the α-band. This corresponds to the activation of the visual cortex responsible for processing visual stimuli and imagination. On the contrary, kinesthetic imagery is characterized by the increasing activity of the motor cortex. We emphasize that Fig. 1 and Fig. 2 show the power distributions averaged over all subjects, and each subject is characterized by a different degree of expression of KI or VI. The contralaterality feature is pronounced only for the KI of the left hand or left leg movement (see Fig. 1*a* and *c*). For the KI of the right hand or right leg movement, we observe bilateral activation of the motor cortex. Thus, the analysis at the source level has shown that kinesthetic imagery is qualitatively similar to performing real movement, and visual imagery is similar to visual processing.

We performed a statistical cluster-based permutation test on the obtained datasets for all subjects and determined significant differences between power distributions corresponding to visual imagery and kinesthetic imagery (see Fig. 3). The statistical test confirmed that the main significant differences are concentrated in the visual and motor cortex of the brain.

Note that both MEG and EEG were used in brain-computer interfaces (BCIs) for training MI classifiers.[37] The authors demonstrated a rather efficient MI classification even without participants' separation into KI and VI categories. Simultaneously, it was shown that KI and VI scenarios affect the classification accuracy, e.g., the accuracy rate obtained for KI was better than for VI.[38] In this context, taking into account the division in KI and VI groups is essential for BCI applications.[6, 39]

5. CONCLUSION

Using the DICS method, we analyzed MEG data from the experiment, where participants performed imaginary movements. We obtained the results at the source level that have confirmed the existence of two types of motor imagery: visual imagery and kinesthetic imagery. We have analyzed and statistically compared averaged distributions of normalized sources power for the VI and KI subgroups of volunteers and identified the main significant differences between these types of motor imagery regarding the excitation of sources of neural activity. The feature of contralaterality is pronounced only for the KI of the left hand or left leg movement. For the KI of the right hand or right leg movement, we observe bilateral activation of the motor cortex. Thus, the analysis at the source level has shown that kinesthetic imagery is qualitatively similar to performing real movement, and visual imagery is similar to visual processing.

6. ACKNOWLEDGMENTS

This work has been supported by RFBR and National Natural Science Foundation of China according to the research project № 19-52-55001. S.K. is supported by the President's Program (Grant MD-1921.2020.9) in the part of the source reconstruction.

REFERENCES

[1] Chholak, P., Niso, G., Maksimenko, V. A., Kurkin, S. A., Frolov, N. S., Pitsik, E. N., Hramov, A. E., and Pisarchik, A. N., "Visual and kinesthetic modes affect motor imagery classification in untrained subjects," *Scientific reports* **9**(1), 1–12 (2019).

[2] Maksimenko, V. A., Kurkin, S. A., Pitsik, E. N., Musatov, V. Y., Runnova, A. E., Efremova, T. Y., Hramov, A. E., and Pisarchik, A. N., "Artificial neural network classification of motor-related eeg: An increase in classification accuracy by reducing signal complexity," *Complexity* **2018** (2018).

[3] Andreev, A. V., Ivanchenko, M. V., Pisarchik, A. N., and Hramov, A. E., "Stimulus classification using chimera-like states in a spiking neural network," *Chaos, Solitons & Fractals* **139**, 110061 (2020).

[4] Danziger, M. M., Moskalenko, O. I., Kurkin, S. A., Zhang, X., Havlin, S., and Boccaletti, S., "Explosive synchronization coexists with classical synchronization in the kuramoto model," *Chaos: An Interdisciplinary Journal of Nonlinear Science* **26**(6), 065307 (2016).

[5] Chholak, P., Pisarchik, A. N., Kurkin, S. A., Maksimenko, V. A., and Hramov, A. E., "Phase-amplitude coupling between mu-and gamma-waves to carry motor commands," in [*2019 3rd School on Dynamics of Complex Networks and their Application in Intellectual Robotics (DCNAIR)*], 39–45, IEEE (2019).

[6] Kurkin, S., Chholak, P., Maksimenko, V., and Pisarchik, A., "Machine learning approaches for classification of imaginary movement type by meg data for neurorehabilitation," in [*2019 3rd School on Dynamics of Complex Networks and their Application in Intellectual Robotics (DCNAIR)*], 106–108, IEEE (2019).

[7] Kurkin, S., Koronovskii, A., and Hramov, A., "Formation and dynamics of a virtual cathode in a tubular electron beam placed in a magnetic field," *Technical Physics* **54**(10), 1520 (2009).

[8] Kurkin, S., Pitsik, E., and Frolov, N., "Artificial intelligence systems for classifying eeg responses to imaginary and real movements of operators," in [*Saratov Fall Meeting 2018: Computations and Data Analysis: from Nanoscale Tools to Brain Functions*], **11067**, 1106709, International Society for Optics and Photonics (2019).

[9] Kurkin, S. A., Pitsik, E. N., Musatov, V. Y., Runnova, A. E., and Hramov, A. E., "Artificial neural networks as a tool for recognition of movements by electroencephalograms.," in [*ICINCO (1)*], 176–181 (2018).

[10] Pisarchik, A. N., Maksimenko, V. A., Andreev, A. V., Frolov, N. S., Makarov, V. V., Zhuravlev, M. O., Runnova, A. E., and Hramov, A. E., "Coherent resonance in the distributed cortical network during sensory information processing," *Scientific Reports* **9**(1), 1–9 (2019).

[11] Kurkin, S., Musatov, V. Y., Runnova, A. E., Grubov, V. V., Efremova, T. Y., and Zhuravlev, M. O., "Recognition of neural brain activity patterns correlated with complex motor activity," in [*Saratov Fall Meeting 2017: Laser Physics and Photonics XVIII; and Computational Biophysics and Analysis of Biomedical Data IV*], **10717**, 107171J, International Society for Optics and Photonics (2018).

[12] Kurkin, S., Maksimenko, V., and Pitsik, E., "Approaches for the improvement of motor-related patterns classification in eeg signals," in [*2019 3rd School on Dynamics of Complex Networks and their Application in Intellectual Robotics (DCNAIR)*], 109–111, IEEE (2019).

[13] Schoffelen, J.-M. and Gross, J., "Source connectivity analysis with meg and eeg," *Human brain mapping* **30**(6), 1857–1865 (2009).

[14] Hramov, A. E., Frolov, N. S., Maksimenko, V. A., Kurkin, S. A., Kazantsev, V. B., and Pisarchik, A. N., "Functional networks of the brain: from connectivity restoration to dynamic integration," *Physics–Uspekhi* , 63 (2020).

[15] Maksimenko, V., Khorev, V., Grubov, V., Badarin, A., and Hramov, A. E., "Neural activity during maintaining a body balance," in [*Saratov Fall Meeting 2019: Computations and Data Analysis: from Nanoscale Tools to Brain Functions*], **11459**, 1145903, International Society for Optics and Photonics (2020).

[16] Badarin, A. A., Skazkina, V. V., and Grubov, V. V., "Studying of human's mental state during visual information processing with combined eeg and fnirs," in [*Saratov Fall Meeting 2019: Computations and Data Analysis: from Nanoscale Tools to Brain Functions*], **11459**, 114590D, International Society for Optics and Photonics (2020).

[17] Hramov, A. E., Pitsik, E. N., Chholak, P., Maksimenko, V. A., Frolov, N. S., Kurkin, S. A., and Pisarchik, A. N., "A meg study of different motor imagery modes in untrained subjects for bci applications.," in [*ICINCO (1)*], 188–195 (2019).

[18] Kurkin, S., Koronovskii, A., and Hramov, A., "Output microwave radiation power of low-voltage vircator with external inhomogeneous magnetic field," *Technical Physics Letters* **37**(4), 356–359 (2011).

[19] Kurkin, S., Chholak, P., Niso, G., Frolov, N., and Pisarchik, A., "Using artificial neural networks for classification of kinesthetic and visual imaginary movements by meg data," in [*Saratov Fall Meeting 2019: Computations and Data Analysis: from Nanoscale Tools to Brain Functions*], **11459**, 1145905, International Society for Optics and Photonics (2020).

[20] Kurkin, S., Hramov, A., Chholak, P., and Pisarchik, A., "Localizing oscillatory sources in a brain by meg data during cognitive activity," in [*2020 4th International Conference on Computational Intelligence and Networks (CINE)*], 1–4, IEEE (2020).

[21] Hassan, M. and Wendling, F., "Electroencephalography source connectivity: aiming for high resolution of brain networks in time and space," *IEEE Signal Processing Magazine* **35**(3), 81–96 (2018).

[22] Jeannerod, M., "The representing brain: Neural correlates of motor intention and imagery," *Behavioral and Brain sciences* **17**(2), 187–202 (1994).

[23] Mizuguchi, N., Nakata, H., Uchida, Y., and Kanosue, K., "Motor imagery and sport performance," *The Journal of Physical Fitness and Sports Medicine* **1**(1), 103–111 (2012).

[24] Kasahara, K., DaSalla, C. S., Honda, M., and Hanakawa, T., "Neuroanatomical correlates of brain–computer interface performance," *Neuroimage* **110**, 95–100 (2015).

[25] Andreev, A., Makarov, V., Runnova, A., and Hramov, A., "Coherent resonance in neuron ensemble with electrical couplings," *Cybernetics and Physics* **6**(3), 135–138 (2017).

[26] Kurkin, S., Badarin, A., Koronovskii, A., and Hramov, A., "The development and interaction of instabilities in intense relativistic electron beams," *Physics of Plasmas* **22**(12), 122110 (2015).

[27] Maksimenko, V. A., Runnova, A. E., Frolov, N. S., Makarov, V. V., Nedaivozov, V., Koronovskii, A. A., Pisarchik, A., and Hramov, A. E., "Multiscale neural connectivity during human sensory processing in the brain," *Physical Review E* **97**(5), 052405 (2018).

[28] Hramov, A. E., Frolov, N. S., Maksimenko, V. A., Makarov, V. V., Koronovskii, A. A., Garcia-Prieto, J., Antón-Toro, L. F., Maestú, F., and Pisarchik, A. N., "Artificial neural network detects human uncertainty," *Chaos: An Interdisciplinary Journal of Nonlinear Science* **28**(3), 033607 (2018).

[29] Taulu, S. and Hari, R., "Removal of magnetoencephalographic artifacts with temporal signal-space separation: demonstration with single-trial auditory-evoked responses," *Human brain mapping* **30**(5), 1524–1534 (2009).

[30] Oostenveld, R., Fries, P., Maris, E., and Schoffelen, J.-M., "Fieldtrip: open source software for advanced analysis of meg, eeg, and invasive electrophysiological data," *Computational intelligence and neuroscience* **2011** (2011).

[31] Groß, J., Kujala, J., Hämäläinen, M., Timmermann, L., Schnitzler, A., and Salmelin, R., "Dynamic imaging of coherent sources: studying neural interactions in the human brain," *Proceedings of the National Academy of Sciences* **98**(2), 694–699 (2001).

[32] Nolte, G., "The magnetic lead field theorem in the quasi-static approximation and its use for magnetoencephalography forward calculation in realistic volume conductors," *Physics in Medicine & Biology* **48**(22), 3637 (2003).

[33] Holmes, C. J., Hoge, R., Collins, L., Woods, R., Toga, A. W., and Evans, A. C., "Enhancement of mr images using registration for signal averaging," *Journal of computer assisted tomography* **22**(2), 324–333 (1998).

[34] Maris, E., "Statistical testing in electrophysiological studies," *Psychophysiology* **49**(4), 549–565 (2012).

[35] Maris, E. and Oostenveld, R., "Nonparametric statistical testing of eeg-and meg-data," *Journal of neuroscience methods* **164**(1), 177–190 (2007).

[36] Tzourio-Mazoyer, N., Landeau, B., Papathanassiou, D., Crivello, F., Etard, O., Delcroix, N., Mazoyer, B., and Joliot, M., "Automated anatomical labeling of activations in spm using a macroscopic anatomical parcellation of the mni mri single-subject brain," *Neuroimage* **15**(1), 273–289 (2002).

[37] Hanna-Leena, H. and Lauri, P., "Across-subject offline decoding of motor imagery from meg and eeg," *Scientific reports* **8**(1), 10087 (2018).

[38] Neuper, C., Scherer, R., Reiner, M., and Pfurtscheller, G., "Imagery of motor actions: Differential effects of kinesthetic and visual–motor mode of imagery in single-trial eeg," *Cognitive brain research* **25**(3), 668–677 (2005).

[39] Maksimenko, V., Badarin, A., Nedaivozov, V., Kirsanov, D., and Hramov, A., "Brain-computer interface on the basis of eeg system encephalan," in [*Saratov Fall Meeting 2017: Laser Physics and Photonics XVIII; and Computational Biophysics and Analysis of Biomedical Data IV*], **10717**, 107171R, International Society for Optics and Photonics (2018).