PROCEEDINGS OF SPIE

SPIEDigitalLibrary.org/conference-proceedings-of-spie

Source-level analysis of age-related differences in the motor initiation phase

Kurkin, Semen, Hramov, Alexander

Semen A. Kurkin, Alexander E. Hramov, "Source-level analysis of age-related differences in the motor initiation phase," Proc. SPIE 12194, Computational Biophysics and Nanobiophotonics, 121940S (29 April 2022); doi: 10.1117/12.2626930

SPIE.

Event: XXV Annual Conference Saratov Fall Meeting 2021; and IX Symposium on Optics and Biophotonics, 2021, Saratov, Russian Federation

Source-level analysis of age-related differences in the motor initiation phase

Semen A. Kurkin[a,b] and Alexander E. Hramov[a,b]

[a]Innopolis University, 1, Universitetskaya str., Innopolis, Russia
[b]Immanuel Kant Baltic Federal University, 14, A. Nevskogo str., Kaliningrad, Russia

ABSTRACT

Based on the results of the EEG experiment in the process of human motor execution, we performed in this paper a source-level analysis of brain activity during the motor initiation phase for two age groups: young and elderly adults. In the theta frequency band, we discovered stronger activation of the contralateral area of the primary motor cortex (Postcentral L and Precentral L zones) for elderly subjects compared to young ones in the right (dominant) hand movements. We discuss the correlation of the obtained source-level results with the known age-related slowing down in the motor initiation before the dominant hand movements. The obtained results are essential for explaining age-related changes in behavioral characteristics, such as reaction time, the accuracy of motor performance, etc.

Keywords: Source-level analysis, EEG, LORETA, age-related changes, motor activity, motor cortex, theta-rhythm

1. INTRODUCTION

The processes occurring in the human brain during motor activity are quite well studied.[1,2] In particular, the standard scenario of brain rhythms dynamics during involuntary movement (on command) is well known: during the first 0.5 s after the command, sensorimotor integration occurs accompanied by the growth of theta-rhythm power over an extensive brain network with maxima in the parietal areas. Then there is the motor activity, which is initiated by desynchronizing the mu-rhythm in the motor cortex. A much less studied urgent problem is the study of age-related changes in the characteristics of this scenario during the performance of motor tasks. The interest in this problem is due, firstly, to the fact that such studies will make it possible to advance the understanding of age-related changes in the brain and, probably, reveal markers of age-related neurodegenerative processes. Such investigations were initiated in work,[3] which has demonstrated at the sensor level that the age-related slowing down in the motor initiation before the dominant hand movement is accompanied by the increased theta activation within the sensorimotor area and reconfiguration of the theta-band functional connectivity in the elderly adults. The properties of the time-frequency and space-time structure of the signals of brain activity neurovisualization are usually analyzed using artificial intelligence methods and statistical analysis.[4–11] However, analysis at the sensor level does not allow one to answer which brain areas are activated when performing a motor task and what age-related differences are observed here.

In this work, we continue this research and conduct source-level analysis. We study the differences in the activation of brain areas between age groups (young vs. elderly) when performing a simple motor activity in the form of clenching the hand into a fist.

Further author information: (Send correspondence to S.A.K.)
S.A.K.: E-mail: kurkinsa@gmail.com

Computational Biophysics and Nanobiophotonics, edited by Dmitry E. Postnov, Boris N. Khlebtsov,
Proc. of SPIE Vol. 12194, 121940S · © 2022 SPIE · 1605-7422 · doi: 10.1117/12.2626930

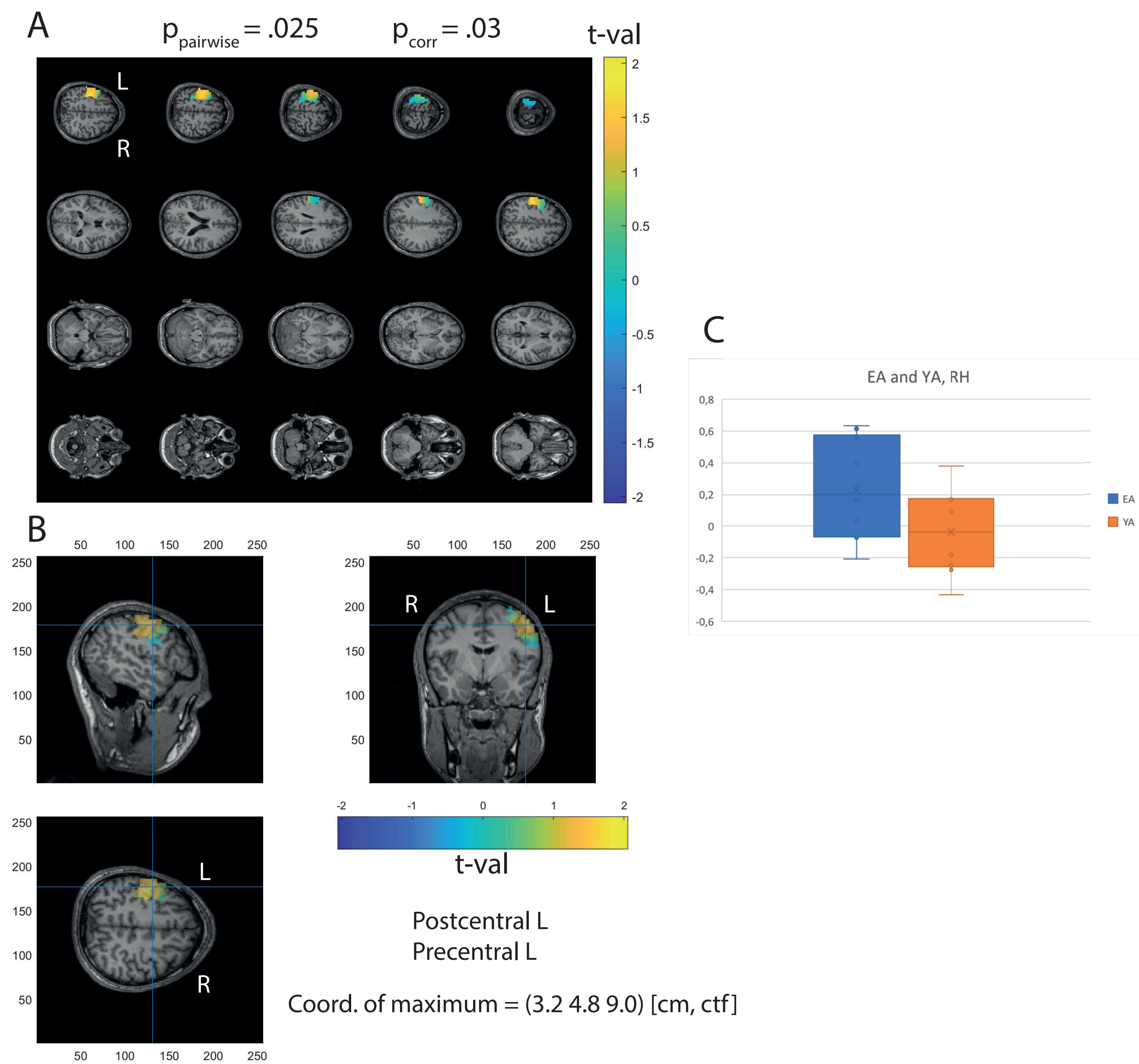

Figure 1. Results of the EEG data source-level analysis. Source plots in slice mode (A) and orthogonal cut view (B) show a positive cluster, reflecting the significant change of the source power (SP) between EA and YA groups on the time interval $t = [0.2, 0.8]\,\mathrm{s}$, for theta-band ($f : 4 - 8\,\mathrm{Hz}$); $p_{corr} = 0.03$ via t-test, corrected for multiple comparisons via the cluster-based test with the Monte-Carlo randomization technique. Legends contain p-values, CTF coordinates of the voxel with maximal t-value, and names of anatomical zones in the cluster according to Automated Anatomical Labeling (AAL). (C) Normalized source power (group mean ±95% CI) in the revealed cluster for EA and YA groups.

2. METHODS

Two groups of healthy volunteers, including 10 elderly adult subjects (EA group; age: 65 ± 5.7 (MEAN±SD); range: 55-72; 4 males, 6 females) and 10 young adult subjects (YA group; age: 26 ± 5.1; range: 19-33; 7 males, 3 females), participated in this study. All subjects were right-handed and had no history of brain tumors, trauma or stroke-related medical conditions. All volunteers were asked to adhere to a healthy lifestyle within 48 hours before the experiment: ensure at least 8 hours of sleep, eliminate alcohol consumption, eliminate or limit consumption of caffeine-containing foods, and avoid excessive physical exertion. The volunteers were familiarized with the experimental procedure in advance and were aware of the possible inconveniences associated with participating in the experiment. Also, they had the opportunity to ask questions of interest and get satisfactory answers to them. Each volunteer completed and signed an informed consent form for participation in the experiment. All experimental works were carried out in accordance with the requirements of the Declaration of Helsinki and approved by the Ethics Commission of Innopolis University.

All participants were instructed to sit on the chair with their hands lying comfortably on the table desk in front of them, palms up. First, we recorded resting state (5 minutes). Further experiment included sequential repetitions of the fine motor task (squeezing one of the hands into a fist after the audio signal and holding it until the second signal) using right (dominant) hand (30 repetitions). Thus, we conducted an experimental study with the Age (EA and YA groups) as between-subject factor. The time interval between the signals during the task and the pause between the repetitions were chosen randomly in the range 4–5 s and 6–8 s, respectively.

We acquired EEG signals using the monopolar registration method (a 10-10 system) with 31 sensors and two reference electrodes on the earlobes and a ground electrode just above the forehead. We used the cup adhesive Ag/AgCl electrodes placed on the "Tien–20" paste (Weaver and Company, USA). Immediately before the experiments started, we performed all necessary procedures to increase skin conductivity and reduce its resistance using the abrasive "NuPrep" gel (Weaver and Company, USA). We controlled the variation of impedance within a range of 2–5 kOhm during the experiment. The electroencephalograph "Encephalan-EEG-19/26" (Medicom MTD company, Russian Federation) with multiple EEG performed amplification and analog-to-digital conversion of the recorded signals.[12–15]

EEG signals were recorded with a sampling rate of 250 Hz and filtered using bandpass (1-70 Hz) and notch (49.5-50.5 Hz) filters. The bandpass filter limits the considered frequency range on the EEG signals and removes low-frequency and high-frequency activities not associated with the EEG. The notch filter removes 50 Hz interference from the power grid. Eyes blinking and heartbeat artifacts removal was performed by the Independent Component Analysis (ICA). Data was then inspected visually and corrected for remaining artifacts.

We applied standardized low-resolution brain electromagnetic tomography (sLORETA) to solve the inverse problem and localize the sources of neuronal activity according to EEG data at each of the predetermined points (voxels) in the brain volume.[16–18] Solving such inverse problems is typical in many areas of physics.[19–24] LORETA is low-resolution brain electromagnetic tomography. This method solves the inverse problem: converting EEG measurements into information about the distribution of neural sources power into a brain volume. The "Colin27" brain MRI averaged template[25] was used to develop a three-layer (brain, skull, and scalp) head model based on a boundary element method (BEM).[26] The sources space inside the brain consisted of 11,865 voxels. The location of the EEG electrodes corresponded to the template head shape.

We analyzed the source characteristics in the predefined time-frequency domain of interest, selected on the basis of the results of the previous analysis.[3] To do this, we reassigned the EEG signals to the total average, subtracted the mean, and filtered with a fourth-order Butterworth $[f_L, f_H]$ Hz band-pass filter, where f_L and f_H define the frequency domain of interest. Then, we performed time-lock averaging across the time interval of interest (TOI) and computed the covariance matrix. The inverse solution yielded estimates of the source power in each voxel, averaged over the selected TOI window. Finally, we normalized the obtained estimates of the power P of each source to the power of EEG resting state EEG as $(P - P_{rest})/P_{rest}$. We used the automated anatomical labeling (AAL) brain atlas[27] to map the location of sources to the anatomical brain regions.

We performed a cluster-corrected statistical between-subject permutation test on the frequency-averaged and TOI-averaged source power distributions to determine significant differences between two groups (EA vs YA).[28] The threshold for paired comparisons with t-test was $p = 0.025$. The p-threshold for the cluster was 0.05. The number of permutations was 2000. Finally, we calculated for each subject the average power of the source activity in the region of the identified cluster for each group. All operations were performed in Matlab using Fieldtrip toolbox.[29]

3. RESULTS

Fig. 1 demonstrates obtained source plots with a positive cluster, reflecting the significant change of the source power between EA and YA groups for theta-band ($f: 4-8$ Hz) on the time interval $t = [0.2, 0.8]$ s. This interval corresponds to the period of command processing and sensorimotor integration. The revealed positive cluster indicates that theta-power in EA is higher than in YA in the Postcentral L and Precentral L zones, which are part of the contralateral (relative to the involved hand) premotor and primary motor cortex (see also Fig. 1C). Thus, theta-band synchronization in this area is higher in EA than YA. This indicates an increased involvement of resources in the process of sensorimotor integration in the elderly adults compared to the young ones.

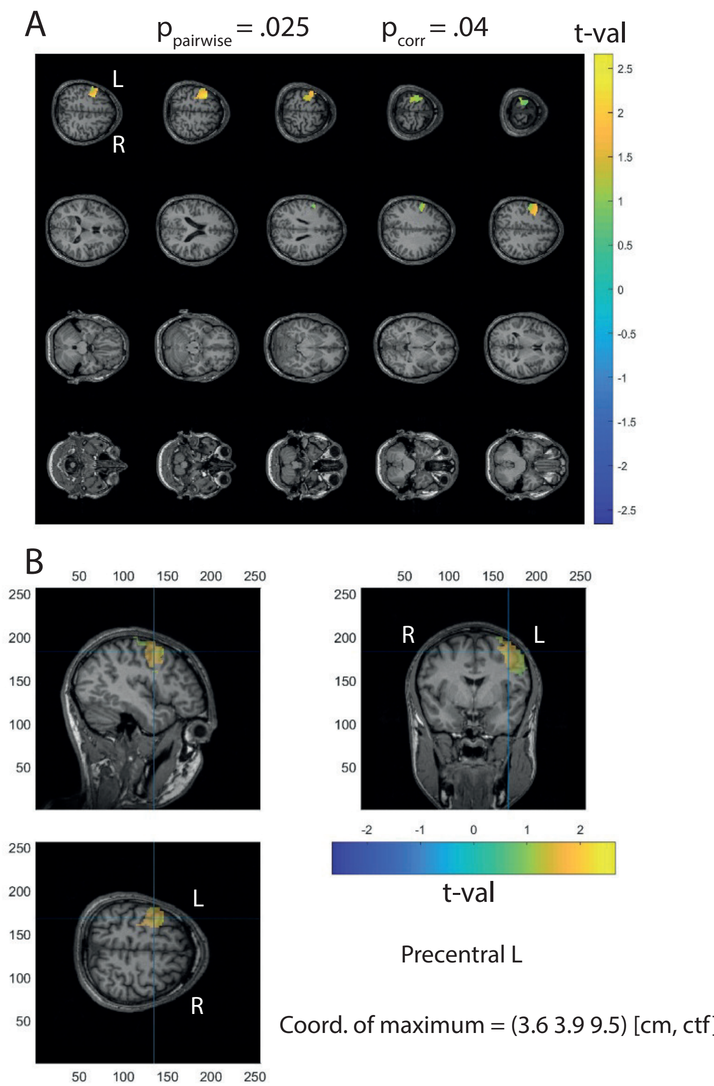

Figure 2. Results of the EEG data source-level analysis. Source plots in slice mode (A) and orthogonal cut view (B) show a positive cluster, reflecting the significant change of the source power (SP) between EA and YA groups on the time interval $t = [0.8, 1.2]\,\mathrm{s}$, for alpha-band ($f : 8 - 14\,\mathrm{Hz}$); $p_{corr} = 0.04$ via t-test, corrected for multiple comparisons via the cluster-based test with the Monte-Carlo randomization technique. Legends contain p-values, CTF coordinates of the voxel with maximal t-value, and names of anatomical zones in the cluster according to Automated Anatomical Labeling (AAL).

Fig. 2 shows source plots with a positive cluster, reflecting the significant change of the source power between EA and YA groups for alpha-band ($f : 8 - 14\,\mathrm{Hz}$) on the time interval $t = [0.8, 1.2]\,\mathrm{s}$. This interval corresponds to the period of the motion execution. The revealed positive cluster indicates that alpha-power in EA is higher than in YA in the Precentral L zone, corresponding to the contralateral primary motor cortex. Thus, alpha-band desynchronization in this area is higher in YA than YA. Since the depth of the alpha rhythm desynchronization is a marker of motor activity, we can conclude that motor activity is more pronounced in the motor cortex in YA compared to EA.

The obtained results support and detail the conclusions made in the work.[3] In particular, an area of the brain (Postcentral L, Precentral L) with increased theta-activation in the elderly in the movement preparation phase was identified. The degraded plasticity in EA requires higher cortical activation for motor planning. YA subjects optimize their cognitive resources for the well-trained motor task accomplishment. The latter was represented as a lower theta-band activation. Therefore, less effective use of cognitive resources slowed the motor planning phase in EA compared to the YA control group during the dominant hand task.

4. CONCLUSION

In the theta frequency band, we discovered stronger activation of the contralateral area of the primary motor cortex (Postcentral L and Precentral L zones) for elderly subjects compared to young ones in the right (dominant) hand movements. Moreover, EA demonstrate stronger activation of the contralateral area of the primary motor cortex in the alpha frequency band. Such results confirm the earlier findings at the sensor-level and should be explained by the different strategies of the motor task initiation between age groups.

ACKNOWLEDGMENTS

This work was supported by the Russian Science Foundation (Grant No. 21-72-10121). S.A.K. was supported by the President Program (MD-590.2022.1.2) in the part of the source reconstruction methods development.

REFERENCES

[1] Hardwick, R. M., Caspers, S., Eickhoff, S. B., and Swinnen, S. P., "Neural correlates of action: Comparing meta-analyses of imagery, observation, and execution," *Neuroscience & Biobehavioral Reviews* **94**, 31–44 (2018).

[2] Hramov, A. E., Frolov, N. S., Maksimenko, V. A., Kurkin, S. A., Kazantsev, V. B., Pisarchik, A. N., et al., "Functional networks of the brain: from connectivity restoration to dynamic integration," *Physics-Uspekhi* **64**(6) (2021).

[3] Frolov, N. S., Pitsik, E. N., Maksimenko, V. A., Grubov, V. V., Kiselev, A. R., Wang, Z., and Hramov, A. E., "Age-related slowing down in the motor initiation in elderly adults," *Plos one* **15**(9), e0233942 (2020).

[4] 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).

[5] 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).

[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., Badarin, A., Grubov, V., Maksimenko, V., and Hramov, A., "The oxygen saturation in the primary motor cortex during a single hand movement: functional near-infrared spectroscopy (fnirs) study," *The European Physical Journal Plus* **136**(5), 1–9 (2021).

[8] Chholak, P., Kurkin, S. A., Hramov, A. E., and Pisarchik, A. N., "Event-related coherence in visual cortex and brain noise: An meg study," *Applied Sciences* **11**(1), 375 (2021).

[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] 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).

[11] 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).

[12] Bukina, T., Khramova, M., and Kurkin, S., "Modern research on primary school children brain functioning in the learning process," *Izvestiya VUZ. Applied Nonlinear Dynamics* **29**(3), 449–456 (2021).

[13] Khramova, M. V., Kuc, A. K., Maksimenko, V. A., Frolov, N. S., Grubov, V. V., Kurkin, S. A., Pisarchik, A. N., Shusharina, N. N., Fedorov, A. A., and Hramov, A. E., "Monitoring the cortical activity of children and adults during cognitive task completion," *Sensors* **21**(18), 6021 (2021).

[14] Kurkin, S. A., Grubov, V. V., Maksimenko, V. A., Pitsik, E. N., Hramova, M. V., and Hramov, A. E., "System for monitoring and adjusting the learning process of primary schoolchildren based on the eeg data analysis," *Information and Control Systems* (5), 50–61 (2020).

[15] 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).

[16] Pascual-Marqui, R. D., "Discrete, 3d distributed, linear imaging methods of electric neuronal activity. part 1: exact, zero error localization," *arXiv preprint arXiv:0710.3341* (2007).

[17] Grech, R., Cassar, T., Muscat, J., Camilleri, K. P., Fabri, S. G., Zervakis, M., Xanthopoulos, P., Sakkalis, V., and Vanrumste, B., "Review on solving the inverse problem in eeg source analysis," *Journal of neuroengineering and rehabilitation* **5**(1), 1–33 (2008).

[18] 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).

[19] Frolov, N. S., Kurkin, S. A., Koronovskii, A. A., Hramov, A. E., and Rak, A. O., "High-efficiency virtual cathode oscillator with photonic crystal," *Applied Physics Letters* **113**(2), 023503 (2018).

[20] Frolov, N. S., Kurkin, S. A., Koronovskii, A. A., and Hramov, A. E., "Nonlinear dynamics and bifurcation mechanisms in intense electron beam with virtual cathode," *Physics Letters A* **381**(28), 2250–2255 (2017).

[21] Kurkin, S., Hramov, A., and Koronovskii, A., "Nonlinear dynamics and chaotization of virtual cathode oscillations in annular electron beam in uniform magnetic field," *Plasma Phys. Rep* **35**(8), 628–642 (2009).

[22] 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), 1520–1528 (2009).

[23] Dubinov, A. E., Petrik, A. G., Kurkin, S. A., Frolov, N. S., Koronovskii, A. A., and Hramov, A. E., "Virpertron: A novel approach for a virtual cathode oscillator design," *Physics of Plasmas* **24**(7), 073102 (2017).

[24] 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).

[25] 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).

[26] Fuchs, M., Kastner, J., Wagner, M., Hawes, S., and Ebersole, J. S., "A standardized boundary element method volume conductor model," *Clinical neurophysiology* **113**(5), 702–712 (2002).

[27] 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).

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

[29] 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).