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Age-related source-level differences in brain activity during motor execution

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Abstract This investigation aimed to expand upon prior knowledge concerning age-related disparities in the motor initiation phase. We operationalized a robust pipeline for identifying source activity, leveraging EEG sensor-level data. Our analytical framework involved a comparative assessment of source activity in both elderly and young adults across distinct laterality aspects of the motor task. Subsequently, we rendered these findings in precise anatomical coordinates and elucidated the underpinnings of the observed disparities. Remarkably, these disparities remained congruent with the contemporary body of knowledge within this domain. Nevertheless, our meticulous application of cluster-based statistical testing yielded no statistically significant distinctions when juxtaposing subjects from varying age groups, hand laterality classifications, and frequency range considerations. Furthermore, we undertook a meticulous examination of the maximal points within clusters demonstrating the most pronounced significance within the elderly and young adult cohorts during tasks involving the right hand. This refined approach unearthed a noteworthy correlation between source power within the theta frequency range and the subjects' age, corroborating existing reference studies and thereby shedding newfound light upon the latent neural mechanisms at play.

1 Introduction

Aging represents a universal phenomenon that began around 3.5 billion years ago with the origin of life. All processes that contribute to the aging can be classified into two major groups: "normal" or, in other words, "healthy" aging is characterized by irreversible and universal physiological changes, while age-related pathologies characterize "abnormal" aging [1].

The weakening of sensorimotor control and functioning is a part of healthy aging. The origins of motor impairments are multivarious, involving abnormalities in the central nervous system, sensory receptors, muscles, and peripheral nerves [2]. Moreover, healthy aging impacts neurological processes by altering the brain's neurochemical and structural features [2]. Aging-related decrease in fine motor control, balance, and gait severely affect the

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ability of older adults to maintain themselves by performing daily routines for their survival and normal existence [3]. Therefore, understanding the cause and markers of impaired motor control mechanisms is essential for improving the life quality of older adults.

While the effects of healthy aging on cortex functioning during execution and control have been widely investigated on both behavioral and neurophysiological levels [4], less is known about how aging influences the motor planning phase. Several premises imply that motor planning is affected by age-related changes. First, many higher cognitive functions, including sensory processing, motor representation, attention, and working memory [5], decline with age. Second, activity in the theta band underpinning most motor functions, including motor planning [6–10], is subjected to age-related alternations [11]. In particular, abnormally elevated theta activity implies cognitive impairment and possible dementia [12, 13].

The authors of Refs. [14–16] showed that age-related changes in the motor planning process influence the slowdown of the motor initiation phase in older adults. Electroencephalography (EEG) was utilized to investigate differences in brain activity during the controlled execution of fine motor tasks between elderly and young adults. The authors demonstrated that the motor cortex of younger adults activated significantly faster during the dominant hand task. Still, the time it took for elderly subjects to engage their motor cortex was the same for both hands and approached the level of the non-dominant hand of younger adults. In elderly and young adults performing the non-dominant hand task, considerable theta-band power was also observed in sensorimotor and frontal areas. At the same time, theta-activation was insignificant in young adults conducting the dominant hand task. This study concluded that motor planning in young and elderly subjects comprises distinct forms of inter-cortical connections, providing age-related changes in motor planning processes based on sensor-level and between-subject functional connectivity analyses [17].

A possible explanation for the observed phenomenon given in the study [14] is the difference in memory exploitation for young and elderly adults during motor tasks. In young adults, initiation of a known motor task activates motor working memory and facilitates a processing of motor memories, i.e., stored knowledge about a motor action gained via experience, to ensure correct motor execution [18]. Working memory access is a speedy and efficient process in terms of cognitive needs [18]. On the other hand, functional connectivity analysis demonstrated a significant coupling between the elderly subjects' motor, frontal, and bilateral temporal areas, with a central localization in the primary motor cortex. Because working memory deteriorates with aging [19], it was expected that memory representation of motor tasks would be less accessible in older persons. As a result, it was shown that the differences in motor planning processes are more demanding and cannot be optimized as efficiently as in younger adults, resulting in significantly delayed motor initiation.

The current study is a logical continuation of the analysis conducted in Ref. [14]. While authors of Ref. [14] employed time-frequency and functional connectivity analyses on a sensor level, the goal we pursued in this study was a broader understanding of the differences in motor preparation and initiation processes in young and elderly adults on a source level. A source reconstruction procedure and source-level statistical analysis were performed using the same EEG data collected and processed in the aforementioned study to broaden the understanding of processes underlying age-related changes in motor functioning.

2 Materials and methods

2.1 Experimental procedure

This study recruited ten healthy elderly adult volunteers (EA group; age: 65 ± 5.69 SD) and ten healthy young adult volunteers (YA group; age: 26.1 ± 5.15 SD). All participants were right-handed and had no prior history of brain tumors, trauma, or stroke-related illnesses.

Subjects sat in a chair with their hands placed on the armrests to avoid non-task-related muscle tension. For the first five minutes, participants were instructed not to think about anything specific, to sit relaxed, and to keep their eyes open while the resting-state EEG signal was recorded. Then an active phase followed where subjects were instructed to perform 60 repetitive fine motor tasks (30 repetitions per hand). Each task involved fist clench after audio signal and holding until the second signal. EEG for both conditions of dominant and non-dominant hands was recorded (right hand, RH, long audio signal and left hand, LH, short audio signal, 750 and 350 ms, respectively). The overall duration of the experimental session was ≈10 min per participant.

2.2 EEG acquisition and preprocessing

Cortical electrical activity was recorded using the EEG acquisition system Encephalan-EEGR-19/26 (Medicom MTD, Taganrog, Russia). A total of 31 Ag/AgCl electrodes were employed in this study, positioned at sites O2, O1, P4, P3, C4, C3, F4, F3, Fp2, Fp1, P8, P7, T8, T7, F8, F7, Oz, Pz, Cz, Fz, Fpz, FT7, FC3, FCz, FC4,

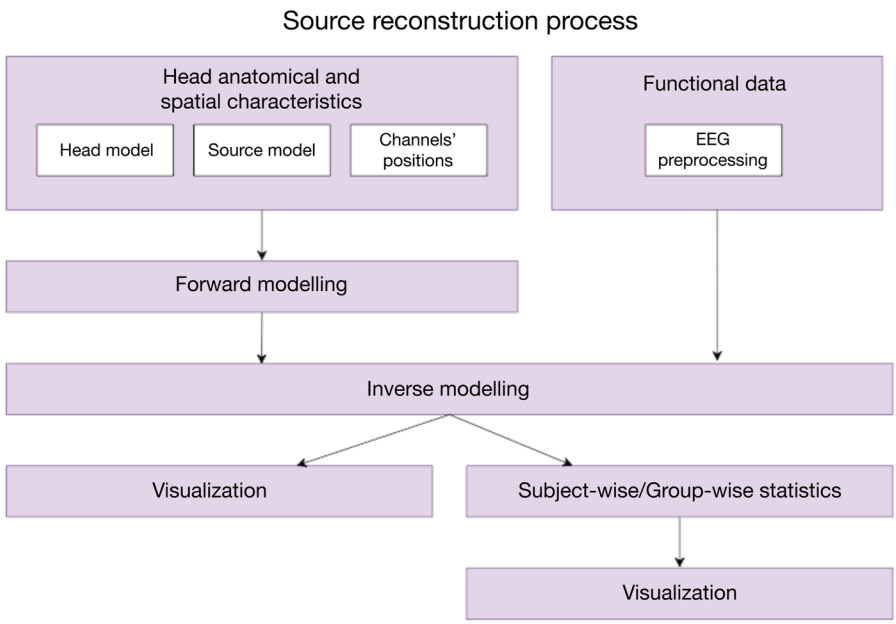

Fig. 1 Flowchart of source reconstruction process

FT8, TP7, CP3, CPz, CP4, and TP8, in accordance with the extended 10-20 electrode placement system [20]. To ensure accurate recordings, two reference electrodes (A1 and A2) were positioned on the earlobes, while a ground electrode was located just above the forehead. Ten-20 paste from Weaver and Company (Aurora, CO, USA) was used to affix the electrodes securely to the scalp.

The EEG signals were sampled at a frequency of 250 Hz (f_s = 250 Hz), and impedance levels were carefully monitored and maintained within the range of 2–5 kΩ throughout the duration of the experiment. Concurrently, electromyography (EMG) signals were recorded from the forearm using the same acquisition hardware to validate the accuracy of the epoch segmentation process.

Preprocessing of the raw EEG data involved several steps. Initially, a 50 Hz Notch filter was applied to attenuate power line interference. Subsequently, a 5th-order Butterworth filter was used to implement bandpass filtering, restricting the frequency range to 1-100 Hz to eliminate low-frequency artifacts. The removal of eye and cardiac artifacts was accomplished through the application of independent component analysis (ICA) [21]. Following artifact removal, the recorded epochs were subjected to manual inspection, and any remaining artifacts were meticulously corrected. Epochs that were deemed unusable due to substantial muscular artifacts were manually excluded from the dataset.

The EEG signals were divided into four conditions according to the combinations of laterality and age conditions: YA LH, YA RH, EA LH, and EA RH. Each epoch was ten seconds long and included 2 s of baseline and 8 s of motor-related activity. Finally, each condition set had at least 15 epochs.

We performed the preprocessing steps using the `MNE` package for Python [22].

2.3 Time intervals of interest and frequencies of interest

The considered in this study time intervals of interest (TOIs), corresponding to the motor preparation and initiation processes, and frequencies of interest (FOIs) are shown in Table 1. We have selected three basic rhythms (frequency ranges) that are known to be involved in the execution of a movement. The choice of TOIs is due to the

Table 1 The studied time intervals of interest (TOIs) and frequencies of interest (FOIs)

Band	Central FOI, Hz	Pre-stimulus TOI, s	Post-stimulus TOI, s	Range, Hz
Theta	6	(−2, −0.2)	(0.0, 0.5)	4–8
Alpha	11	(−2, −0.2)	(0.5, 1.5)	8–14
Beta	22	(−2, −0.2)	(0.5, 1.5)	14–30

known characteristic dynamics of the rhythms. Thus, approximately in the first 0.5 s after the command, there is synchronization of the theta rhythm, which is then followed by desynchronization in the alpha and beta ranges.

We divided all the epochs into pre- and post-stimulus intervals and truncated them by respecting TOI for each subject, hand condition, and three frequency bands. In both pre- and post-intervals, we averaged the trials belonging to the same subject, condition, and frequency band to increase the signal-to-noise ratio (SNR).

2.4 Source-level analysis

In the case of EEG, a source-level activity is determined by the following components:

- EEG signals recorded on the scalp;
- the EEG sensors' spatial configuration;
- geometrical and electrical characteristics of a head;
- general spatial characteristics of anatomical brain sources.

Consequently, two major steps comprise the source estimation process:

- Forward modeling, which is the estimation of the potential or field distribution for the known source configuration and the head model;
- Inverse modeling, which is the process of estimating unknown sources that match the recorded EEG.

The whole process of brain source reconstruction is shown in Fig. 1. We utilized FieldTrip Toolbox in MATLAB [23] for the source-level analysis.

The first step in the source reconstruction process is solving the so-called forward problem by modeling the scalp potential distribution based on source configuration in a head model. This volume conduction model or head model is represented in FieldTrip as a structure with electromagnetic properties of the tissue. It represents the head's geometry, the tissue's conductivity, and its mathematical parameters. Deriving these parameters depends on a computational approach to forward modeling. We used the Boundary Element Method (BEM) as such method due to its computational effectivity. BEM tries to fit boundary values into the integral equation using the specified boundary conditions represented by tissue-to-tissue interfaces rather than values across the whole space defined by a partial differential equation. The integral equation can then be employed to numerically calculate the solution directly at any specified location inside the solution domain. Therefore, given the information about head surfaces that act like boundaries in BEM solution, this method provides electromagnetic characteristics of the interface between head skin, skull, and brain similar to the real one. We used symmetric BEM approach implemented in OpenMEEG software [24] to generate a conductivity model. As a result, we got a triangulated mesh data structure with conductivity value for each surface and a matrix used for the volume conduction model.

Due to a lack of MRI resources, we used the one template MRI representation of the head model for all subjects. This model [25] was developed as a semi-realistic head model that provides accurate information about the brain-skull interface and generalizes human head properties. As a result of MRI segmentation process, we received a description of each surface represented in coordinates of voxels and its belonging to one of the three tissue types (brain, skull, or scalp) and received structures of each surface represented by coordinates of vertices connected in a triangular way.

We used Nz, LPA, and RPA electrodes as MRI landmarks positions to align electrodes in CTF coordinates of anatomical MRI. As a result, we got electrodes placed in the needed positions regarding the head model.

We applied sLORETA as the technique for an inverse solution because it was identified as the best one in terms of both localization error and computational cost. As a result, we computed a spatial filter and estimated the power amplitude of the sources at each point in the head volumes for every (subject, condition, frequency band) combination. We normalized the post-stimulus source power distributions with the baseline (pre-stimulus) time interval using "percent" mode, i.e., subtracting the mean of the baseline values followed by dividing by the mean of baseline values.

2.5 Statistical analysis

We analyzed power distributions of identified sources and compared source activity for EA and YA groups in the same conditions (RH and LH). Therefore, the so-called between-subject design on independent samples was utilized.

While performing statistical analysis of EEG data, one always has to deal with multiple comparisons problem (MCP) due to its multidimensional structure. In our case, we have vast arrays of estimated source power for each subject. Moreover, such arrays represent voxels arranged in a head volume with their own spatial organization. The MCP emerges from a vast number of pairwise comparisons of power in such voxels.

Table 2 Results of the source-level statistical analysis for the clusters with maximal significance for each group, condition, and frequency band

	Theta	Alpha	Beta
YA vs EA, RH condition			
Cluster p value	0.14	0.22	0.24
Cluster t value sum	−800.3	−525.7	507.7
YA vs EA, LH condition			
Cluster p value	0.36	0.23	0.217
Cluster t value sum	188.9	−632.97	708.2
RH vs LH, YA group			
Cluster p value	0.14	–	–
Cluster t value sum	−1097.7	–	–
RH vs LH, EA group			
Cluster p value	–	–	–
Cluster t value sum	–	–	–

While many solutions help to deal with MCP [26], due to the spatial organization of data being under comparison, the so-called Monte Carlo approach is an appropriate solution for this case [27]. The Monte Carlo technique solves MCP by calculating cluster statistics and identifying the significance of a particular cluster.

Another statistical technique we employ is the significance testing of source power estimation at a point. For this purpose, the point of maximum significance should be chosen in the cluster of interest. Then, all the source power values of all subjects in a particular condition (LH or RH) at that point are sampled. In that way, we obtain typical one-dimensional arrays for both EA and YA groups, on which we perform standard significance testing — t test.

Also, we built a linear regression model for the points of maximum significance and calculated Pearson correlation coefficient between power amplitude and the subject's age.

3 Results

The Table 2 contains the results of statistical analysis of source-level data for different groups, conditions, and frequency bands. There are no significant differences for all the (group, condition, frequency)-combinations. The most significant difference underlies the right-hand activity in the theta band of the YA and EA groups and the activity of the YA group in the theta band in RH and LH conditions. For the (YA vs. EA, RH, theta) comparison, there were two clusters with almost identical p-values (0.14 and 0.15). Moreover, in this case, the most significant point belonged to the second cluster. So that, we took into consideration both clusters for the (YA vs. EA, RH, theta) condition. All the visualizations for these three clusters are presented in Fig. 2.

We performed a point-wise analysis of the power amplitudes of points with the most significant difference among the three clusters. We discovered a significant difference in the power amplitudes between groups (for the first two clusters EA vs. YA, RH condition) and conditions (YA, RH vs. LH). Boxplots visualizing the differences between groups (EA vs. YA, RH condition), scatter plots, and the lines obtained in the regression analysis between the cluster power and age are presented in Fig. 3 for the first two clusters. Boxplot visualizing the differences between the conditions (RH vs. LH, YA) is presented in Fig. 4. In the Table 3, we demonstrated the results of the significance and correlation analysis.

4 Discussion

Although we did not find any significant differences in the sources' power distributions, it is important to look at and interpret activity in the brain regions in which the maximum difference between groups/conditions was observed. As for the difference in source activation between EA and YA groups using the right hand, the brain activity in the theta band of the EA group was broader and had higher amplitude in the prefrontal cortex. These findings confirm the results in [14] about the increased amplitude of activity of elderly adults in the theta band,

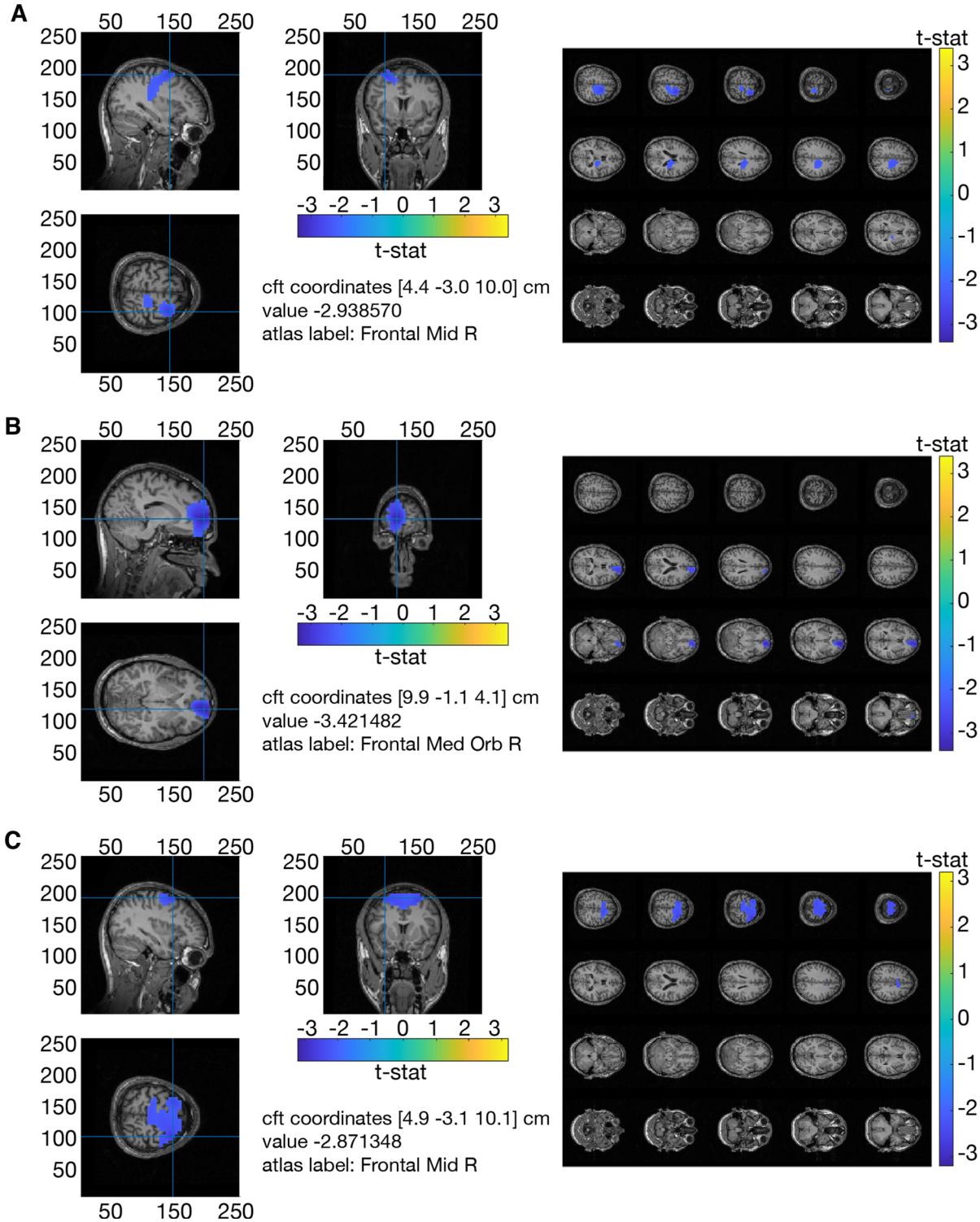

Fig. 2 Ortho-representations (left) and slice representations (right) for: **A** – the first most significant cluster, YA vs. EA, RH condition, theta band; the point of maximal significance is in the right middle frontal gyrus. **B** – the second most significant cluster YA vs. EA, RH condition, theta band; the point of maximal significance is in the right orbitofrontal cortex. **C** – the third most significant cluster RH vs. LH, YA group, theta band; the point of maximal significance is in the right middle frontal gyrus

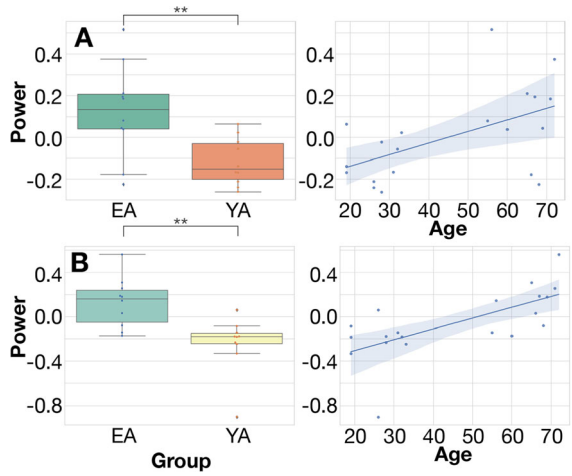

Fig. 3 Boxplots for means comparison (Left), scatter plots, and the lines obtained in the regression analysis between the age and cluster power (Right) for the points of maximal significance: **A** – right middle frontal gyrus from Cluster 1; **B** – orbitofrontal cortex from Cluster 2. The clusters were obtained in the YA vs. EA test for the RH condition, theta band. "**" denote statistically significant differences with $p < 0.003$

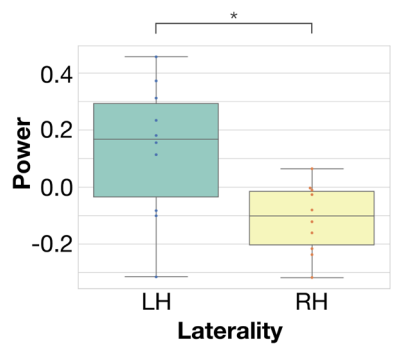

Fig. 4 Boxplot for means comparison for the point of maximal significance (right middle frontal gyrus) from Cluster 3 obtained in the LH vs. RH test for the YA group, theta band. "*" denotes statistically significant difference with $p = 0.0125$

in particular, about the strong connectivity of this area with the motor cortex. Thus, the data at the source level broaden the understanding of the differences in the nature of motor initiation in elderly and young adults.

Moreover, the complete absence of significant clusters when comparing the source activity in the theta band of elderly adults in the right- and left-handed motor task and the same significance level of differences in the case of (YA vs. EA, RH condition, theta band) and (YA, RH vs. LH, theta band) confirm assumptions about the age-related deterioration of motor function and so-called developed ambidexterity in elderly adults in many previous studies [4, 28]. The results demonstrated in [29] explain this effect by use-dependent plasticity: due to sedentary lifestyles and reduced motor activity in old age, the standard networks used for motor activity degrade. Thus, a compensatory mechanism is formed that engages and reorganizes the networks not typical for a motor activity to maintain motor function in the elderly.

The most significant area in the second cluster, the orbitofrontal cortex, which is part of the prefrontal cortex, is precisely one of the uncharacteristic areas of the brain for motor activity, and it is also one of the hubs of the central execution network (CEN). The CEN, in turn, is responsible for decision-making, controlled processing, and the integration of information from other brain networks. Also, the region of the most significance in the first cluster, the right middle frontal gyrus, is responsible for attention and its reorienting [30]. Thus, motor activity in the elderly creates stronger and broader connectivity of different brain networks, is modulated by CEN to maintain their connectivity, and requires a more conscious inclusion and attention in performing a motor task. Moreover, a recent study [31] has shown that CEN is greatly influenced by a normal aging process and represents a significant marker of aging, which also supports these findings.

The difference in amplitude of activity at the source level across groups of different ages in both clusters, as well as between the right and left hands of young adults, is the first important conclusion that emerges from the point-wise analysis. Since we normalized data as the difference between post-stimulus and pre-stimulus activity divided

Table 3 Point-level statistics results – two-paired p-value, Pearson correlation coefficient (r), and p-value (p) of correlations between the power amplitude and age

Cluster #	p value	EA & YA – r, p
1	0.0096	0.537, 0.014
2	0.0029	0.67, 0.0012
3	0.0125	–

by pre-stimulus activity, this distinction indicates that the source power increased in the case of elderly people, while for younger people, it decreased in contrast. Thus, there was theta-synchronization after the stimulus in the EA group, and in YA one, there was observed theta-desynchronization. These findings also prove our conclusions about more concentration and attention involved in the brain activity of elderly people and the non-dominant hand-using condition of young people. Both these cases are comparable in terms of power, which also allows assuming developed ambidexterity to be the reason for the observed effect.

Another notable effect is the revealed correlation between the age of the subjects and the power at the points of the most significant difference. In both clusters from comparing EA and YA groups in RH condition, there is a significant correlation between age and source power for merged YA and EA groups. These findings support the conclusion about increased theta activity in elderly adults and extend it by introducing the dependency coefficient between age and source power.

The main limitation of the study is the data used for analysis. Although the sample sizes and the number of channels in the EEG were sufficient to detect significant differences at the sensor level, the source reconstruction procedure is more demanding. Another limitation is that we used a universal anatomical MRI model for all subjects, which also affected the accuracy of source reconstruction due to not considering the anatomical features of the subjects' heads.

5 Conclusion

This study aimed to extend our knowledge about age-related alternations in motor planning. We carried out EEG source-level analysis and studied the markers of age-related changes. We analyzed activity in three different frequency bands. In analysis, we compared the sources in older and young adults at different laterality of the motor task, provided its anatomical visualization and interpretation of mechanisms implying these differences. However, we found no statistically significant difference comparing subjects between the groups, hand laterality, and frequency ranges using cluster-based statistics. Nevertheless, we compared the most significant points in the clusters in young and older adults using the right hand in the task for more sophisticated analysis. This analysis revealed a significant correlation between source power in the theta range and the age of the subjects.

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Availability of data and materials The data presented in this study are available on request from the corresponding author.

References

1. R.C. Atchley, A continuity theory of normal aging. Gerontologist **29**(2), 183–190 (1989)
2. F.A. Sorond, Y. Cruz-Almeida, D.J. Clark, A. Viswanathan, C.R. Scherzer, P. De Jager, A. Csiszar, P.J. Laurienti, J.M. Hausdorff, W.G. Chen et al., Aging, the central nervous system, and mobility in older adults: neural mechanisms of mobility impairment. J. Gerontol. Ser. A Biomed. Sci. Med. Sci. **70**(12), 1526–1532 (2015)
3. R.D. Seidler, J.A. Bernard, T.B. Burutolu, B.W. Fling, M.T. Gordon, J.T. Gwin, Y. Kwak, D.B. Lipps, Motor control and aging: links to age-related brain structural, functional, and biochemical effects. Neurosci. Biobehav. Rev. **34**(5), 721–733 (2010)
4. S. Heuninckx, N. Wenderoth, S.P. Swinnen, Systems neuroplasticity in the aging brain: recruiting additional neural resources for successful motor performance in elderly persons. J. Neurosci. **28**(1), 91–99 (2008)

5. A. Ikkai, C.E. Curtis, Common neural mechanisms supporting spatial working memory, attention and motor intention. Neuropsychologia **49**(6), 1428–1434 (2011)
6. S. Kurkin, S. Gordleeva, A. Savosenkov, N. Grigorev, N. Smirnov, V.V. Grubov, A. Udoratina, V. Maksimenko, V. Kazantsev, A.E. Hramov, Transcranial magnetic stimulation of the dorsolateral prefrontal cortex increases posterior theta rhythm and reduces latency of motor imagery. Sensors **23**(10), 4661 (2023)
7. A. Badarin, V. Antipov, V. Grubov, N. Grigorev, A. Savosenkov, A. Udoratina, S. Gordleeva, S. Kurkin, V. Kazantsev, A. Hramov, Psychophysiological parameters predict the performance of naive subjects in sport shooting training. Sensors **23**(6), 3160 (2023)
8. E. Pitsik, N. Frolov, K. Hauke Kraemer, V. Grubov, V. Maksimenko, J. Kurths, A. Hramov, Motor execution reduces EEG signals complexity: Recurrence quantification analysis study. Chaos Interdisc. J. Nonlinear Sci. **30**(2), 023111 (2020)
9. S. Kurkin, A. Badarin, V. Grubov, V. Maksimenko, A. Hramov, The oxygen saturation in the primary motor cortex during a single hand movement: functional near-infrared spectroscopy (fnirs) study. Eur. Phys. J. Plus **136**(5), 548 (2021)
10. A. Chepurova, A. Hramov, S. Kurkin, Motor imagery: How to assess, improve its performance, and apply it for psychosis diagnostics. Diagnostics **12**(4), 949 (2022)
11. N. Frolov, E. Pitsik, V. Grubov, A. Badarin, V. Maksimenko, A. Zakharov, S. Kurkin, A. Hramov, Perceptual integration compensates for attention deficit in elderly during repetitive auditory-based sensorimotor task. Sensors **23**(14), 6420 (2023)
12. F. Quandt, M. Bönstrup, R. Schulz, J.E. Timmermann, M. Zimerman, G. Nolte, F.C. Hummel, Spectral variability in the aged brain during fine motor control. Front. Aging Neurosci. **8**, 305 (2016)
13. E. Stomrud, O. Hansson, L. Minthon, K. Blennow, I. Rosén, E. Londos, Slowing of eeg correlates with csf biomarkers and reduced cognitive speed in elderly with normal cognition over 4 years. Neurobiol. Aging **31**(2), 215–223 (2010)
14. N.S. Frolov, E.N. Pitsik, V.A. Maksimenko, V.V. Grubov, A.R. Kiselev, Z. Wang, A.E. Hramov, Age-related slowing down in the motor initiation in elderly adults. PLoS ONE **15**(9), 0233942 (2020)
15. G. Guyo, A. Pavlov, E. Pitsik, N. Frolov, A. Badarin, V. Grubov, O. Pavlova, A. Hramov, Cumulant analysis in wavelet space for studying effects of aging on electrical activity of the brain. Chaos, Solitons & Fractals **158**, 112038 (2022)
16. E.N. Pitsik, N.S. Frolov, N. Shusharina, A.E. Hramov, Age-related changes in functional connectivity during the sensorimotor integration detected by artificial neural network. Sensors **22**(7), 2537 (2022)
17. A.E. Hramov, N.S. Frolov, V.A. Maksimenko, S.A. Kurkin, V.B. Kazantsev, A.N. Pisarchik, Functional networks of the brain: from connectivity restoration to dynamic integration. Phys. Usp. **64**(6), 584 (2021)
18. A. Dahan, R. Bennet, M. Reiner, How long is too long: an individual time-window for motor planning. Front. Hum. Neurosci. **13**, 238 (2019)
19. R. Quentin, L.G. Cohen, Reversing working memory decline in the elderly. Nat. Neurosci. **22**(5), 686–688 (2019)
20. M.R. Nuwer, G. Comi, R. Emerson, A. Fuglsang-Frederiksen, J.-M. Guérit, H. Hinrichs, A. Ikeda, F.J.C. Luccas, P. Rappelsburger, Ifcn standards for digital recording of clinical eeg. Electroencephalogr. Clin. Neurophysiol. **106**(3), 259–261 (1998)
21. A. Hyvärinen, E. Oja, Independent component analysis: algorithms and applications. Neural Netw. **13**(4–5), 411–430 (2000)
22. A. Gramfort, M. Luessi, E. Larson, D.A. Engemann, D. Strohmeier, C. Brodbeck, R. Goj, M. Jas, T. Brooks, L. Parkkonen et al., Meg and eeg data analysis with mne-python. Front. Neurosci. **7**, 267 (2013)
23. R. Oostenveld, P. Fries, E. Maris, J.-M. Schoffelen, Fieldtrip: open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data. Comput. Intell. Neurosci. **2011**, 1–9 (2011)
24. A. Gramfort, T. Papadopoulo, E. Olivi, M. Clerc et al., Forward field computation with OpenMEEG. Comput. Intell. Neurosci. **2011**, 1–13 (2011)
25. C.J. Holmes, R. Hoge, L. Collins, R. Woods, A.W. Toga, A.C. Evans, Enhancement of mr images using registration for signal averaging. J. Comput. Assist. Tomogr. **22**(2), 324–333 (1998)
26. A. Narkevich, K. Vinogradov, A. Grjibovski, Multiple comparisons in biomedical research: the problem and its solutions. Ekologiya cheloveka (Hum. Ecol.) **27**(10), 55–64 (2020)
27. E. Maris, R. Oostenveld, Nonparametric statistical testing of eeg-and meg-data. J. Neurosci. Methods **164**(1), 177–190 (2007)
28. T. Kalisch, C. Wilimzig, N. Kleibel, M. Tegenthoff, H.R. Dinse, Age-related attenuation of dominant hand superiority. PLoS ONE **1**(1), 90 (2006)
29. C.M. Bütefisch, B.C. Davis, S.P. Wise, L. Sawaki, L. Kopylev, J. Classen, L.G. Cohen, Mechanisms of use-dependent plasticity in the human motor cortex. Proc. Natl. Acad. Sci. **97**(7), 3661–3665 (2000)
30. S. Japee, K. Holiday, M.D. Satyshur, I. Mukai, L.G. Ungerleider, A role of right middle frontal gyrus in reorienting of attention: a case study. Front. Syst. Neurosci. **9**, 23 (2015)
31. K. Fang, S. Han, Y. Li, J. Ding, J. Wu, W. Zhang, The vital role of central executive network in brain age: evidence from machine learning and transcriptional signatures. Front. Neurosci. **15**, 733316 (2021)