Network analysis of electrical activity in brain motor cortex during motor execution and motor imagery

Pitsik, Elena, Frolov, Nikita

Elena Pitsik, Nikita Frolov, "Network analysis of electrical activity in brain motor cortex during motor execution and motor imagery," Proc. SPIE 11459, Saratov Fall Meeting 2019: Computations and Data Analysis: from Nanoscale Tools to Brain Functions, 1145908 (9 April 2020); doi: 10.1117/12.2563976

Event: Saratov Fall Meeting 2019: VII International Symposium on Optics and Biophotonics, 2019, Saratov, Russian Federation

Network analysis of electrical activity in brain motor cortex during motor execution and motor imagery

Elena Pitsik[1], Nikita Frolov[1]

[1]Neuroscience and Cognitive Technology Laboratory, Center for Technologies in Robotics and Mechatronics Components, Innopolis University, 420500, Innopolis, The Republic of Tatarstan, Russia

ABSTRACT

We conducted the functional connectivity analysis of EEG recordings corresponding to motor execution and motor imagery. This study aims at finding the relationship between motor actions and neuronal interactions in different low-frequency bands: μ/α (8-13 Hz) and β (15-30 Hz). To reveal functional networks in mentioned frequency bands we develop and apply the novel model-free approach based on wavelet and recurrence analysis of multivariate time-series.

Keywords: recurrence quantification analysis, electroencephalography, motor execution, motor imagery, recurrence-based measure of dependence, connectivity analysis

1. INTRODUCTION

The development of new methods for motor-related brain activity identification and quantification is of strong demand due to a social significance, i.e. neurorehabilitation, motor skills training, sports etc.[1–3] It is known that event-related desynchronization (ERD) or suppression of μ-oscillations (8-13 Hz) in somatosensory brain cortex is a hallmark of motor-related activity in magneto- and electroencephalographic (M/EEG) data.[4–6] Traditionally, methods of time-frequency analysis are used to detect ERD in EEG oscillations.[7,8] Besides, techniques based on artificial intelligence were successfully applied to detection of various EEG/MEG patterns.[9–11]

At the same time, it is known that most processes of normal brain activity, including motor imagery and motor execution, are subserved by neuronal interactions between remote brain areas.[12] Mostly, connectivity analysis on M/EEG recordings is implemented using simple model-based (Pearson's correlation) or model-free (Imaginary part of coherency) approaches that take into account linear dependencies.[13–16]

In this work, we test the novel approach to explore nonlinear directed dependencies in EEG data based on the recurrence plots (RPs) and their quantification. RP was introduced for the analysis of short nonstationary time series based on the visualization of the recurrences inherent for many dynamical systems. Quantification of RPs has been successfully applied in climate research,[17,18] analysis of biological data,[19,20] and neuroscience .[21–23]

In present paper, we use Recurrence-based Measure of Dependence, which is based on the concepts and methods of nonlinear dynamics.[24,25] We consider typical brain connectivity patterns localized in the motor cortex during motor execution and motor imagery tasks. Particularly, we are interested in brain connectivity differences between these two types of tasks in μ (8-13 Hz) and β (15-30 Hz) bands, which are known to be associated with planning and executioin of motor-related brain activity.

2. METHODS

2.1 Experimental study

Our experimental dataset consisted of EEG recordings of motor execution and motor imagery with upper limbs. The task was to clench the fist after the first audio signal and relax it after the second one for motor execution (long audio signal for the left hand and short — for the right). For motor imagery, only one audio command was used to mark the task onset. The timing of both types of task was as follows:

Further author information: (Send correspondence to Elena Pitsik)
Elena Pitsik: E-mail: e.pitsik@innopolis.ru

Saratov Fall Meeting 2019: Computations and Data Analysis: from Nanoscale Tools to Brain Functions, edited by Dmitry E. Postnov, Proc. of SPIE Vol. 11459, 1145908 · © 2020 SPIE
CCC code: 1605-7422/20/$21 · doi: 10.1117/12.2563976

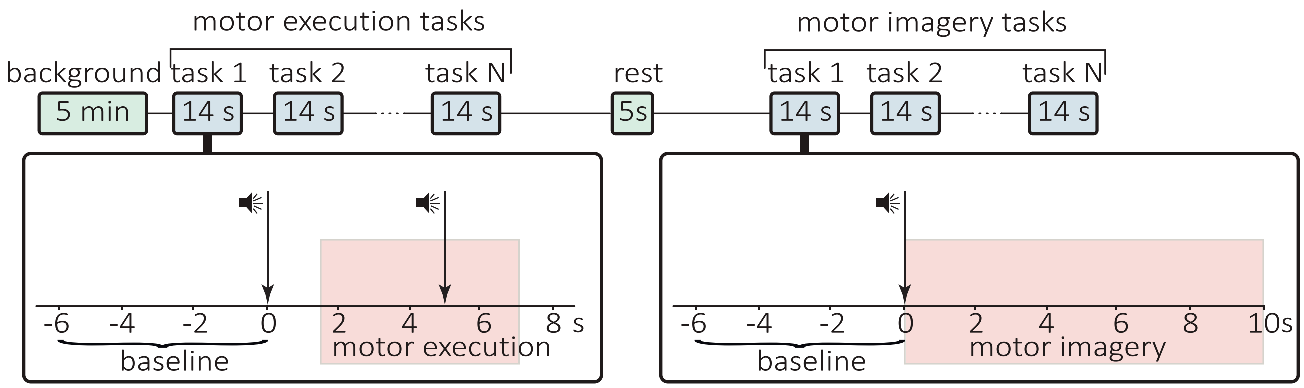

Figure 1. Experimental procedure for motor execution and motor imagery.

1. Motor execution: 4-5 seconds between two same signals (the start and the end of the task), 6-8 seconds between the second signal of the previous task and first signal of the next.
2. Motor imagery: 7-10 seconds between the trials.

EMG signals recorded from both hands were used during data preparation to locate the exact moment of motor execution.

To record both EEG and EMG we used EEG/EMG system ''Encephalan-EEGR-19/26" (Medicom MTD company, Taganrog, Russian Federation). Signals were sampled at $fs = 250$ Hz and filtered with 50 Hz Notch filter. In further analysis, we used EEG signal recorded with 12 Ag/AgCl electrodes placed over the sensorimotor cortex and frontal lobe (F3, Fz, F4, Fc3, Fcz, Fc4, C3, Cz, C4, Cp3, Cpz, Cp4) according to the international "10–10" system.

15 subjects were participated in the experiments, all of them healthy, in the age of 18–33 years and never experienced BCI-based training. Each EEG recording was filtered with 4^{th} order Butterworth band-pass filter in the range 1-100 Hz, and then sliced on 14-second trials (6 before first audio signal and 8 after). Experiment lasted approximately 30 minutes and included 30 movements with each hand, real as well as imaginary. Audio commands for two types of movements were presented randomly in order to avoid the adaptation effect.

2.2 Connectivity analysis

In present paper, we applied a novel approach to connectivity analysis based on recurrences. Let us describe it following Goswami et al.[24] Recurrence plot (RP) is a visual representation of binary matrix $R_{i,j}$:

$$R_{i,j} = \Theta(\epsilon_i - ||x_i - x_j||), x_i \in \mathbb{R}^m, i, j = 1...N, \tag{1}$$

where x_i and x_j are the embedded trajectories in the reconstructed phase space of the signal, ϵ_i is a recurrence threshold, Θ is a Heaviside function and $|| \cdot ||$ is a function for distance calculation, or norm (Euclidean norm was used in present paper). Therefore, $R_{i,j} = 1$ means that trajectories x_j belongs to the x_i's ϵ-neighborhood and can be considered as similar states of the signal $X(t)$.

RP consists of the various structures formed by the recurrence points, which can be quantified to get an access to the hidden features of signal's complexity. The basic measure of RP is a recurrence rate defined as the probability $P(x_i)$ of any trajectory x_i to recur, which is the sum of all recurrence points of the recurrence matrix:

$$P(x_i) = \frac{1}{N^2} \sum_{i=1}^{N} R_{i,j} \tag{2}$$

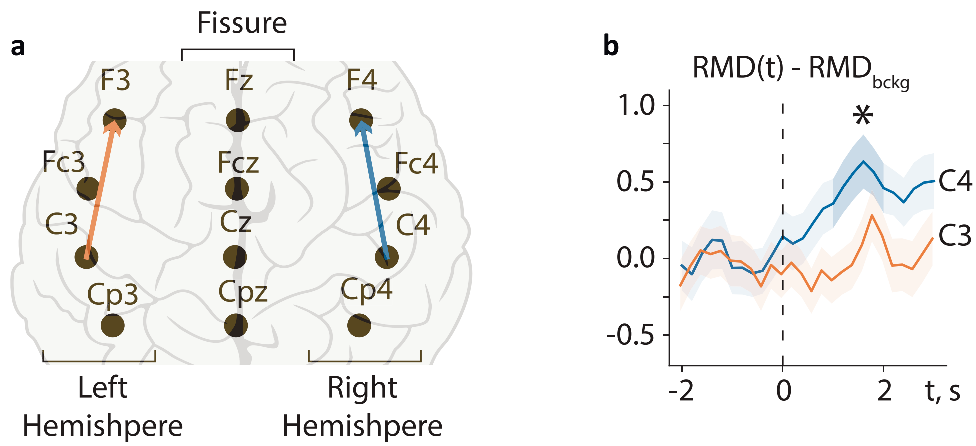

Figure 2. (a) Arrangement of considered set of electrodes located over the motor cortex and the frontal lobe; (b) RMD calculated for channels $C4-F4$ and $C3-F3$ with the baseline RMD excluded.

To evaluate the influences that different brain areas might have on each other during motor-related activity processing, we calculated joint recurrence plot for different groups of channels:

$$JR_{i,j} = \Theta(\epsilon_x - ||x_i - x_j||)\Theta(\epsilon_x - ||y_i - y_j||), x_i, y_i \in \mathbb{R}^m, i, j = 1...N, \tag{3}$$

and define the joint probability that two considered states x_i and y_i recur simultaneously:

$$P_{x_i,y_i} = \frac{1}{N}\sum_{j=1}^{N} JR_{i,j}, \tag{4}$$

Finally, we define coupling strength between sensors as Recurrence-based Measure of Dependence:

$$RMD_i = \frac{P(x_i, y_i)}{P(x_i)P(y_1)}, \tag{5}$$

Note that RMD_i cannot detect the direction of X and Y dependencies. Therefore, we used log-mean $RMD(\tau)$ with τ as a lag in one of the system:

$$RMD(\tau) = \log_2\left(\frac{1}{N'}\sum_{i=1}^{N'} RMD_i(\tau)\right), \tag{6}$$

Here, $N' = N - \tau$, RMD_i as measure of dependence for y_i lagged at τ units: $y_i = y_i(\tau)$.

2.3 Statistical test

We used nonparametric statistical t-test based on random partitions to compare time-dependent RMD at different experimental conditions (baseline vs motor task). The selection of statistical method is due to the multiple comparison problem (MCP) caused by unknown location of significant differences between considered conditions.[26]

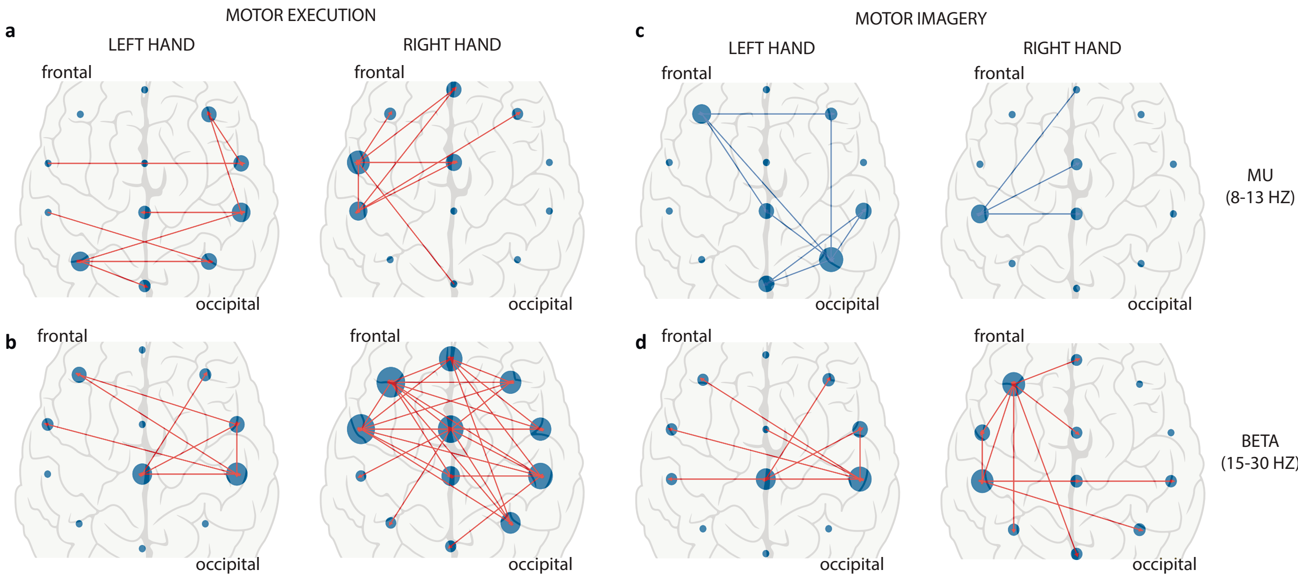

Figure 3. Results of connectivity analysis of motor-related tasks for right and left hands in (a,c) μ-band and (b,d) β-band. The color of the connectivity arrows illustrates links having significantly increasing (red) or decreasing (blue) coupling strength.

3. RESULTS

Fig. 2 illustrates the RMD calculation for the contralateral links (C3-F3 and C4-F4) during left hand movement execution. We consider time-dependent RMD distribution over trials with excluded baseline level RMD_{bckg} (2 s before command). We see that during the left hand motor execution the coupling strength significantly increases in the right hemisphere, while motor-related changes in left-hemisphere coupling are insignificant (shaded area in fig. 2b marked with $*$ for C4-F4 link). This is consistent with well-known contralaterality feature of motor-related brain activity.

Further, we analyze between-subject properties of functional connectivity in different frequency bands. Fig. 3(a-b) presents the results for motor execution with right and left hands in μ and β bands, respectively. One can see clear contralateral pattern emerging in μ-band during movement execution (Fig. 3a). Moreover, for the left hand movement execution the most strong connections are concentrated in right motor and premotor cortex (channels Cp3, Cp4, Cpz, Cz, C4), whereas for the right hand the activation of left motor and frontal areas take place (channels Fc3, Fcz, F3, F4, Fz, C3). At the same time, interactions in β-band are strongly associated with frontal and motor areas without pronounced lateralization.

We see that motor imagery demonstrates quite different connectivity patterns. In both right and left hand, motor imagery shows decreasing contralateral RMD in μ-band. However, in β band the connectivity increases, providing the same contralateral pattern as on fig. 3a: the most pronounced connectivity increase is observed at motor and frontal cortex in the left hand and in motor and premotor for the right hand.

4. CONCLUSION

We have analyzed neuronal interactions in brain motor cortex associated with motor execution and motor imagery in two distinct frequency bands — μ (8-13 Hz) and β (15-30 Hz) — using novel recurrence-based technique. Provided sensor-level connectivity analysis uncovered contralateral patterns related with increasing coupling between left hemisphere sensors during right hand movements in both frequency bands and vice versa. During motor execution neuronal interactions in μ-band involve sensors located in the motor and the premotor areas, wheres β-band interactions are associated with the frontal and the motor areas.

In contrast with motor execution, motor imagery is associated with cotralateral coupling decrease in μ-band, while β-band connectivity increases in approximately the same way that occurs during motor execution.

In our opinion, obtained results are valuable for further studies of functional connectivity of remote brain areas during motor execution and motor imagery. Moreover, presented method will be useful for further investigation of motor-related pattern formation on M/EEG data.

5. ACKNOWLEDGMENTS

This work has been supported by the Center for Technology in Robotics and Mechatronics Components (Innopolis University).

REFERENCES

[1] Daly, J. J. and Wolpaw, J. R., "Brain–computer interfaces in neurological rehabilitation," *The Lancet Neurology* **7**(11), 1032–1043 (2008).

[2] Frolov, A. A., Mokienko, O., Lyukmanov, R., Biryukova, E., Kotov, S., Turbina, L., Nadareyshvily, G., and Bushkova, Y., "Post-stroke rehabilitation training with a motor-imagery-based brain-computer interface (bci)-controlled hand exoskeleton: a randomized controlled multicenter trial," *Frontiers in neuroscience* **11**, 400 (2017).

[3] Pisarchik, A. N., Maksimenko, V. A., and Hramov, A. E., "From novel technology to novel applications: Comment on "an integrated brain-machine interface platform with thousands of channels" by elon musk and neuralink," *Journal of medical Internet research* **21**(10), e16356 (2019).

[4] Neuper, C., Wörtz, M., and Pfurtscheller, G., "Erd/ers patterns reflecting sensorimotor activation and deactivation," *Progress in brain research* **159**, 211–222 (2006).

[5] Maksimenko, V. A., Pavlov, A., Runnova, A. E., Nedaivozov, V., Grubov, V., Koronovskii, A. A., Pchelintseva, S. V., Pitsik, E., Pisarchik, A. N., and Hramov, A. E., "Nonlinear analysis of brain activity, associated with motor action and motor imaginary in untrained subjects," *Nonlinear Dynamics* **91**(4), 2803–2817 (2018).

[6] 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).

[7] Pavlov, A., Grishina, D., Runnova, A., Maksimenko, V., Pavlova, O., Shchukovsky, N., Hramov, A., and Kurths, J., "Recognition of electroencephalographic patterns related to human movements or mental intentions with multiresolution analysis," *Chaos, Solitons & Fractals* **126**, 230–235 (2019).

[8] Maksimenko, V. A., Lüttjohann, A., Makarov, V. V., Goremyko, M. V., Koronovskii, A. A., Nedaivozov, V., Runnova, A. E., van Luijtelaar, G., Hramov, A. E., and Boccaletti, S., "Macroscopic and microscopic spectral properties of brain networks during local and global synchronization," *Physical Review E* **96**(1), 012316 (2017).

[9] 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).

[10] 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).

[11] 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).

[12] Schnitzler, A. and Gross, J., "Normal and pathological oscillatory communication in the brain," *Nature reviews neuroscience* **6**(4), 285 (2005).

[13] Bastos, A. M. and Schoffelen, J.-M., "A tutorial review of functional connectivity analysis methods and their interpretational pitfalls," *Frontiers in systems neuroscience* **9**, 175 (2016).

[14] Makarov, V. V., Zhuravlev, M. O., Runnova, A. E., Protasov, P., Maksimenko, V. A., Frolov, N. S., Pisarchik, A. N., and Hramov, A. E., "Betweenness centrality in multiplex brain network during mental task evaluation," *Physical Review E* **98**(6), 062413 (2018).

[15] 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).

[16] Frolov, N. S., Maksimenko, V. A., Khramova, M. V., Pisarchik, A. N., and Hramov, A. E., "Dynamics of functional connectivity in multilayer cortical brain network during sensory information processing," *The European Physical Journal Special Topics* **228**(11), 2381–2389 (2019).

[17] Adeniji, A., Olusola, O., and Njah, A., "Comparative study of chaotic features in hourly wind speed using recurrence quantification analysis," *AIP Advances* **8**(2), 025102 (2018).

[18] Bai, A., Hira, S., and Deshpande Parag, S., "Recurrence based similarity identification of climate data," *Discrete Dynamics in Nature and Society* **2017** (2017).

[19] Ahmad, S. A. and Chappell, P. H., "Surface emg classification using moving approximate entropy," in [*2007 International Conference on Intelligent and Advanced Systems*], 1163–1167, IEEE (2007).

[20] Acharya, U. R., Faust, O., Sree, S. V., Ghista, D. N., Dua, S., Joseph, P., Ahamed, V. T., Janarthanan, N., and Tamura, T., "An integrated diabetic index using heart rate variability signal features for diagnosis of diabetes," *Computer methods in biomechanics and biomedical engineering* **16**(2), 222–234 (2013).

[21] Acharya, R., Faust, O., Kannathal, N., Chua, T., and Laxminarayan, S., "Non-linear analysis of eeg signals at various sleep stages," *Computer methods and programs in biomedicine* **80**(1), 37–45 (2005).

[22] Acharya, U. R., Sree, S. V., Chattopadhyay, S., Yu, W., and Ang, P. C. A., "Application of recurrence quantification analysis for the automated identification of epileptic eeg signals," *International journal of neural systems* **21**(03), 199–211 (2011).

[23] Maksimenko, V. A., Frolov, N. S., Hramov, A. E., RUNNOVA, A. E., Grubov, V. V., Kurths, J., and Pisarchik, A. N., "Neural interactions in a spatially-distributed cortical network during perceptual decision-making," *Frontiers in behavioral neuroscience* **13**, 220 (2019).

[24] Goswami, B., Marwan, N., Feulner, G., and Kurths, J., "How do global temperature drivers influence each other?," *The European Physical Journal Special Topics* **222**(3-4), 861–873 (2013).

[25] Ramos, A. M., Builes-Jaramillo, A., Poveda, G., Goswami, B., Macau, E. E., Kurths, J., and Marwan, N., "Recurrence measure of conditional dependence and applications," *Physical Review E* **95**(5), 052206 (2017).

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