Motor-related elderly brain activity revealed via recurrence quantification analysis

Elena Pitsik
Neuroscience and Cognitive Technology Laboratory
Innopolis University
Innopolis, Russia
0000-0003-1850-2394

Nikita Frolov
Neuroscience and Cognitive Technology Laboratory
Innopolis University
Innopolis, Russia
0000-0002-2788-1907

Anton Kiselev
Department of New Cardiological Informational Technologies
Saratov State Medical University
Saratov, Russia
0000-0003-3967-3950

Nikolai Shchukovskii
Department of Nervous Diseases
Saratov State Medical University
Saratov, Russia
0000-0001-5995-0922

Artem Badarin
Neuroscience and Cognitive Technology Laboratory
Innopolis University
Innopolis, Russia
0000-0002-3212-5890

Vadim Grubov
Neuroscience and Cognitive Technology Laboratory
Innopolis University
Innopolis, Russia
0000-0003-2491-2592

***Abstract*—We study motor-related brain activity in the group of elderly individuals (aged 55-76) using the continuous wavelet transform and the recurrence quantification analysis (RQA). Detecting motor patterns on electroencephalograms (EEGs) is a complex task due to the nonstationarity and complexity of EEG signal, which leads to the high inter- and intra-subject variability of traditionally applied methods. It is especially demanded to use these methods in the context of the elderly group analysis due to the additional age-related changes of the brain motor cortex functioning. In the present paper, we show that RQA measure of complexity is very useful in detection of transitions from background (normal) to motor-related brain activity captured via EEG signals. Moreover, used RQA measure of determinism calculated to quantify brain processes during upper limbs movements reflects contralateral properties of motor-related neuronal activity, which is helpful at distinguishing between two types of executed movements.**

***Index Terms*—recurrence quantification analysis, neurorehabilitation, age-related effects, brain-computer interface, event-related desynchronization, electroencephalography**

I. Introduction

Development of new methods for motor-related brain activity identification and quantification is of strong demand due to its social significance, i.e. in the area of neurorehabilitation, motor skills training, sports etc. [8], [10], [23]. It is known that event-related desynchronization (ERD) or suppression of μ-oscillations (8-13 Hz) in somatosensory brain cortex is the hallmark of the motor-related activity in magneto- and electroencephalographic (M/EEG) data [17], [20]. Most studies use the data obtained from healthy young individuals aged 18-40. However, in the context of neurorehabilitation, it is important to explore the motor activity of elderly groups, because the age-related changes of brain plasticity significantly affect the neuronal processes underlying cognitive and motor-related brain activity. In the present paper, we perform our analysis within the group of elderly participants aged 55-76 and compare the obtained results with our earlier study [24].

Traditionally, methods of time-frequency analysis are used to detect ERD in EEG signal [20], [21]. Usually, ERD patterns are easily observed from the averaged data, but may be hardly identified from single trials due the nonstationarity and complexity of EEG signals or inter- and intra-subject variability. Thus, single-trial analysis requires extracting highly relevant features and application of the advanced mathematical tools for their identification. In the present paper we use averaged spectral power of EEG signals corresponding to the motor execution to reveal how ERD pattern is formed in the group of elderly individuals. Besides, we propose a strategy for the analysis of signal complexity based on the recurrence quantification analysis (RQA). RQA was introduced in 1994 [26] to perform the analysis of recurrences emerging in dynamical systems. RQA was successfully applied in the climate research [4], [6], analysis of biological data [2], [5] and neuroscience [1], [3]. In the present paper, we use RQA

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to analyze the complexity of the motor-related EEG.

In particular, we use windowed calculation of the RQA measure of determinism (DET) to reveal the transitions of EEG time series from the background (normal) to motor-related brain activity. We show that the motor action causes the reduction of random fluctuations inherent in the background brain activity and triggers more regular and deterministic behavior, which is considered as another evidence of motor-related processes.

II. Materials and methods

A. Dataset

In the present research we used dataset containing EEG and EMG data of 15 right-handed subjects (7 female). All participants were relatively healthy, aged 55-76 and had no history of nervous system injuries and had never participated in BCI-based training.

We used the same experimental paradigm described in [24]. Subjects were sitting in a comfortable chair and performed two types of movements according to commands:

1) first short audio signal (1 s): squeeze left hand into fist, hold it tight until the second short signal, and relax it after;
2) first long audio signal (1.5 s): squeeze right hand into fist, hold it tight until the second long signal, and relax it after.

Subjects performed 30 movements with each hand. Commands were presented randomly in order to avoid the adaptation effect.

The intervals between two tasks (end of the previous task and beginning of the next) were randomly chosen in the range 6-8 seconds. The time intervals for one task accomplishment was also selected randomly in the range 4-5 seconds.

Raw EEG signals were filtered using highpass filter with cutoff frequency of 1 Hz to exclude low-frequency artifacts. Specific artifacts as eye-movements, blinking and heartbeat were removed using independent component analysis (ICA) [13]. Then, all recordings were additionally filtered in the range 8-14 Hz using fifth-order Butterworth bandpass filter. Finally, we collected 30 epochs for each type of executed upper limb movements (18 second long, 6 seconds baseline).

B. Equipment

During the experimental session, we recorded 31-channel EEG layout using the noninvasive EEG/EMG system "Encephalan-EEGR-19/26" (Medicom MTD company, Taganrog, Russian Federation) with sampling rate fs = 250 Hz. Ag/AgCl EEG electrodes were located on the scalp according to the "10-10" International electrode system. In the present study, we used the subset of 6 EEG electrodes covering the left and right hemispheres of the brain motor cortex (Fc3, Fc4, C3, C4, Cp3, Cp4).

To record the muscle electrical activity, we used 2 electromyography (EMG) electrodes for each hand (1 reference and 1 recording). EMG signals were used to determine the exact moments of the motor executions for each participant during the data preparation and were not used for further analysis.

C. Time-frequency analysis

On the first step of our study we analyzed the spectral power of the obtained epochs for each subject. We used the continuous wavelet transform (CWT):

$$W(f,t_0) = \sqrt{f}\int_{-\infty}^{+\infty} x(t)\psi^*(f(t-t_0))dt \qquad (1)$$

with $*$ representing complex conjugation and ψ — the mother function:

$$\psi(\eta) = \frac{1}{\sqrt[4]{\pi}} e^{i\omega_0\eta} e^{\frac{-\eta^2}{2}} \qquad (2)$$

as a complex Morlet wavelet, which is widely used in the analysis of neurophysiological signals [12]. Here, $i = \sqrt{-1}$ and $\omega_0 = 2\pi$ – central frequency of the Morlet wavelet.

Then, obtained wavelet coefficients were averaged over the μ-rhythm (8-14 Hz) and the θ-rhythm (4-8 Hz):

$$W_\mu(t) = \int_{f\in\phi} W(f,t)dt \qquad (3)$$

Each of presented subsets of multivariate time series is considered as a 3D-trajectory. We use this method of state space trajectory construction to avoid the single variable embedding problem [7], [14]–[16].

CWT along with the EEG preprocessing steps was performed using MNE package for Python [11].

D. Recurrence quantification analysis

The idea of recurrence plots (RP) uses the natural property of many dynamical processes to recur. These recurrences are represented as the neigbouring points of the reconstructed phase space trajectory. Two states x_i and x_j of the system $\mathbf{X}$ are considered similar, if they enter each other's ϵ-neighborhood. Therefore, to visualize them, we construct binary matrix $R_{i,j}$:

$$R_{i,j} = \Theta(\epsilon_i - ||x_i - x_j||), x_i \in \mathbb{R}^m, i,j = 1...N, \qquad (4)$$

where Θ is a Heaviside function, ϵ_i is a recurrence threshold, $||\cdot||$ is a norm, and N is a number of considered stated x_i [25]. Resulting recurrence matrix $R_{i,j}$ contains various structures, such as diagonal and vertical lines, which quantification allows to uncover hidden dynamical regimes of the system.

In the present paper, we estimate the RQA measure of determinism (DET) in a 3-sec floating window (750 data points). Determinism is quantified as follows:

$$DET = \frac{\sum_{l=l_{min}}^{N} lR_{i,j}(\epsilon)}{\sum_{l=1}^{N} lR_{i,j}(\epsilon)}, \qquad (5)$$

with $l_{min} = 2$ – minimal considered length of the diagonal line. A diagonal line in RP means that the system's state repeatedly passes along its past trajectory for a finite time

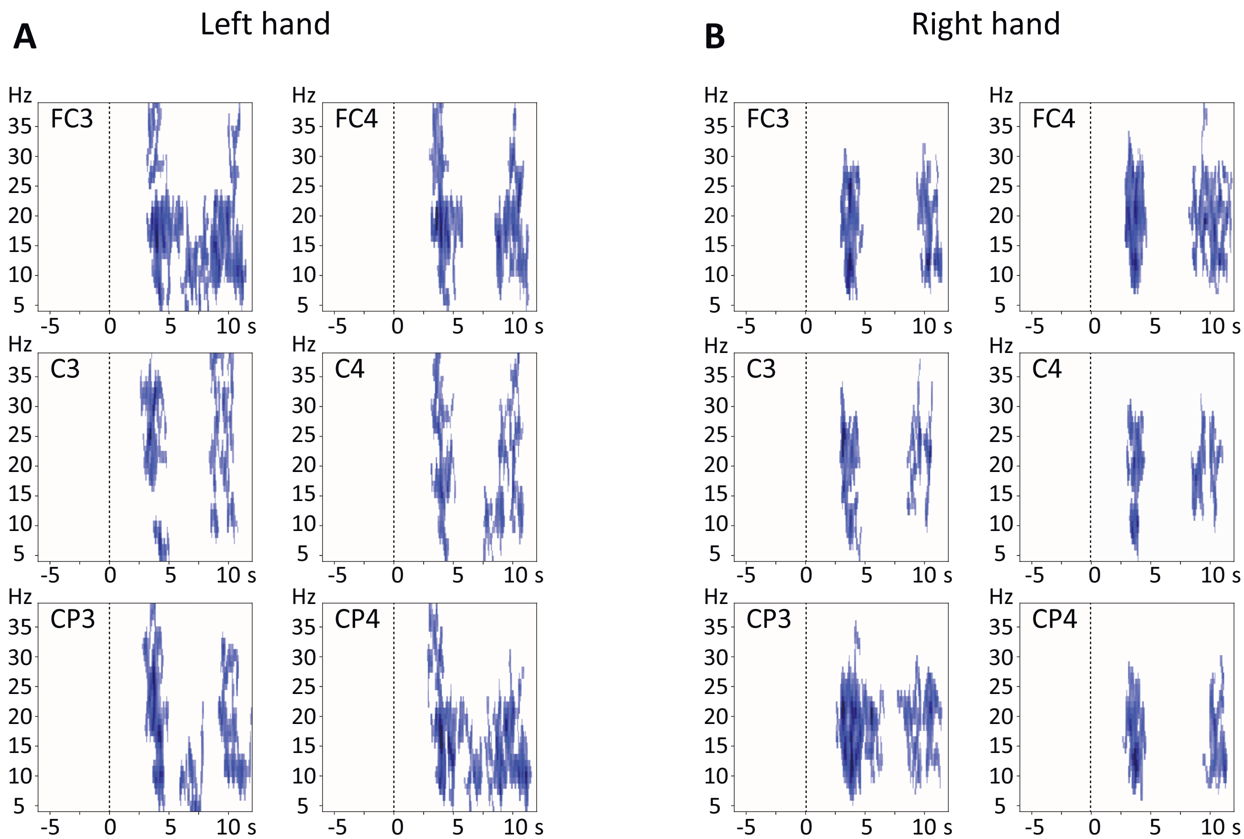

Fig. 1. Event-related desynchronization (ERD) in the brain motor cortex during the left hand (A) and right hand (B) motor executions in the time frequency domain. Blue areas highlight the significant spectral power decrease as compared to the preceding baseline level.

interval equal to the length of a diagonal line. Therefore, DET quantifying the percentage of the recurrence points forming diagonal structures of RP is a parameter describing the regularity of the process. The less chaotic the time series is, the longer diagonal lines it causes on the RP.

In this study we considered EEG epochs as a set of two three-dimensional multivariate subsets representing right and left hemispheres of the brain motor cortex:

1) right hemisphere (RH): $\mathbf{X}_R(t) = (x_{Cp4}(t), x_{C4}(t), x_{Fc4}(t))^{\mathrm{T}}$;
2) left hemisphere (LH): $\mathbf{X}_L(t) = (x_{Cp3}(t), x_{C3}(t), x_{Fc3}(t))^{\mathrm{T}}$;

RQA has been performed using pyunicorn package for Python [9].

III. Results

At the first stage we calculated spectral power of EEG time series corresponding to the motor executions performed by the elderly people. We used non-parametric cluster-based analysis with random partitions to detect the areas of statistically significant ERD in the time-frequency domain as described in [19]. Fig. 1 shows the results of our calculations. Both right and left hands movements cause significant ERD shortly after the audio command (marked as vertical dashed line at 0). Note that the most pronounced ERD is observed in the frequency range 10-25 Hz covering both μ (8-14 Hz) and β (15-30 Hz) bands. It is also important that contralaterality of ERD traditionally found in the primary motor area M1 (sensors C3 and C4) is not observed in the group of the elderly participants [22]. In contrast, the primary somatosensory cortex (sensors CP3 and CP4) demonstrate well-pronounced contralateral ERD cluster in both left and right hand movements. Therefore, one can access age-related changes of brain motor-activity by comparing these results for elderly group and our previous results for young subjects. For example, it is known that β-activity has a tend to increase with age [18].

Next, we use $\mathbf{X}_R(t)$ and $\mathbf{X}_L(t)$ subsets to analyze the complexity of the motor-related EEG. For each participant, we average time dependencies of DET over the epochs and exclude the averaged baseline level (3 seconds before the audio command). The results are shown in Fig. 2. First, the DET time dependence reaches two maxima corresponding to the first and second motor actions (hand squeezing and relaxing). We also observe the presence of significant differences between left and right hemisphere during the right hand movement. Moreover, the peak of DET is pronounced in left hemisphere, which is consistent with the well-known effect of contralaterality of the brain motor activity. However, such effect is insignificant in the case of the left hand movement.

Finally, we considered the difference between the left and

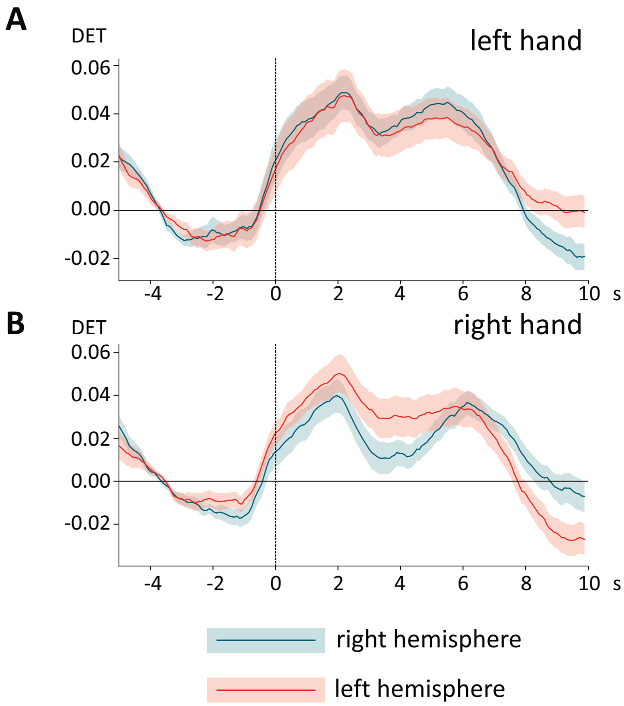

Fig. 2. DET time dependence averaged over the epochs (mean±SE) for the left hand (A) and right hand (B) movements calculated in the right hemisphere (blue) and left hemisphere (red).

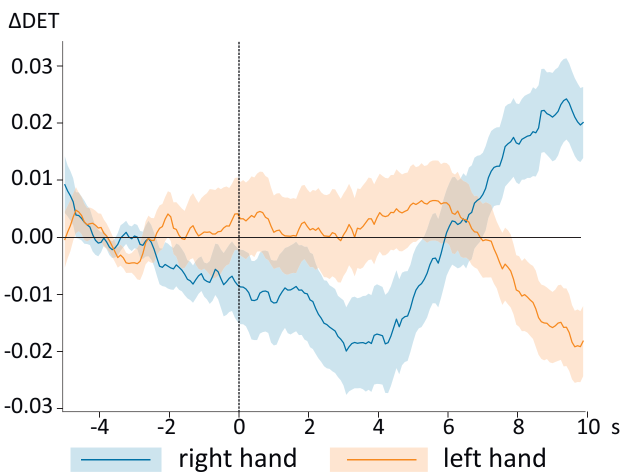

Fig. 3. Difference between DET in the right and left hemisphere in the case of the right hand (blue) and left hand (orange) movements.

right brain hemisphere for each hand. One can see from Fig. 3, the contralateral effect is observed in the motor-related EEG of elderly group only in the case of right hand movements: while ΔDET for the right hand takes negative values, the ΔDET for the left hand fluctuates near the zero-level. Therefore, features revealed via RQA measures of complexity, such as DET, can be used for classification of two types of movements using EEG time series.

IV. Conclusions

We revealed important features of motor-related EEG of elderly people using time-frequency analysis and recurrence quantification analysis. An important result is that motor-related ERD pattern in elderly people is observed rather in β-band that μ-band, and is pronounced in CP-channels. Moreover, we repeated our earlier result [24] and confirmed on another group of subjects, that motor-related EEG is indeed associated with decrease of signals complexity and suppression of random fluctuation. Despite the fact the effect of contralaterality is not pronounced as good as with healthy young individuals, this study made an important contribution in research of aging effects of brain EEG patterns formation and plasticity.

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