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Features of motor-related brain activity revealed via recurrence quantification analysis

Elena Pitsik[1], Nikita Frolov[1]

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

ABSTRACT

We propose an approach for motor-related brain activity analysis based on the combination of continuous wavelet transform and recurrence quantification analysis (RQA). Detecting such patterns on EEG is a complex task due to the nonstationarity and complexity of EEG signal, which leads to high inter- and intra-subject variability of traditionally applied methods. We show that RQA measures of complexity, such as recurrence rate an laminarity, are very useful in detection of transitions from background to motor-related EEG. Moreover, RQA measures time dependence for upper limbs is contralateral, which allows us to distinguish two types of movements.

Keywords: RQA, wavelet transform, recurrence plots, electroencephalography, ERD

1. INTRODUCTION

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.[4,5] Traditionally, methods of time-frequency analysis are used to detect ERD in EEG oscillations.[6,7] Besides, techniques based on artificial intelligence were successfully applied to detection of various EEG/MEG patterns.[8–10] However, direct recognition of motor activity in real time is sometimes problematic due to the high inter- and intra-subject variability inherent for this pattern.[11] Usually, ERD patterns are easily observed from averaged data, but may be hardly identified from single trials due the nonstationarity and complexity of EEG signals. Thus, single-trial analysis requires extracting more relevant features and application of advanced mathematical tools for their identification.

Summarizing the above, we propose a strategy for motor-related pattern analysis based on recurrence quantification analysis (RQA). RQA was introduced in 1994[12] for numerical analysis of recurrences emerging in dynamical systems. RQA has been successfully applied in climate research,[13,14] analysis of biological data,[15,16] and neuroscience .[17,18] In present paper, we use RQA to analyze periodicities emerging in motor-related EEG.

We hypothesize, that background (random) brain activity is associated with large-amplitude and incoherent fluctuations of spectral power in μ-band. In turn, motor-related task accomplishment is characterized by stabilization of these fluctuations. With this goal in mind we applied recurrence quantification analysis (RQA) and wavelet analysis to identify such transitions of μ-band spectral power dynamics. In course of the study, we show that combined wavelet transform and RQA appear to be a relevant mathematical approaches for detection of motor-related activity. In particular, results of RQA prove our hypothesis and reveal that motor task execution is accompanied by the significant increase of recurrence rate (RR) and laminarity (LAM) of μ-band spectral power time-series indicating the suppression of random fluctuations. Moreover, we prove the inter-subject robustness of proposed method and show that RQA measures are contralateral, which allows to distinguish two types of motor execution (right and left hands).

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

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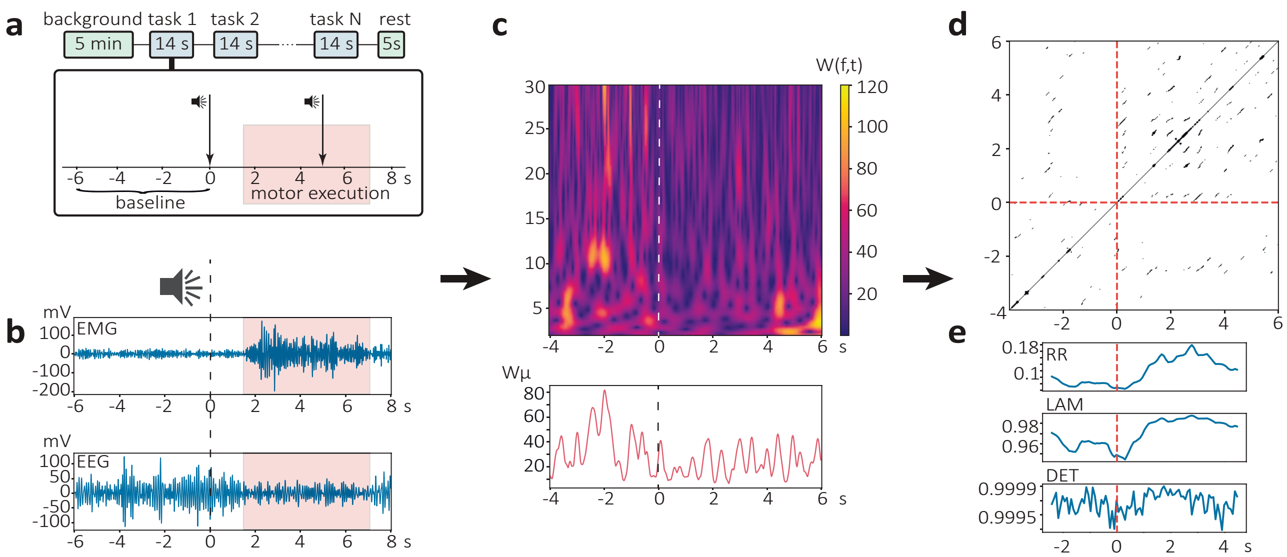

Figure 1. Representation of the used method. (a) Experimental design and the scheme of single trial. Time intervals between the signals within trial were ranged between 4–5 seconds, and 6–8 seconds from the second signal of the previous and the first signal of the next task; (b) samples of EMG and EEG recordings from the experimental dataset. For illustrative purposes, the EEG trial was filtered in the μ-rhythm range; (c) Wavelet surface of the corresponding EEG trial and the averaged μ-rhythm spectral power W_μ; (d) Recurrence plot of the corresponding time series W_μ and (e) windowed RQA measures. For all panels, dashed line represents the audio signal.

2. METHODS

2.1 Experimental data

Experimental setup included recording of EEG and EMG of both hands as well. We used EEG/EMG system Encephalan-EEGR-19/26 (Medicom MTD company, Taganrog, Russian Federation) with 250 Hz sampling frequency and 50 Hz Notch filtering. In further analysis, we used EEG signal recorded with 9 Ag/AgCl electrodes placed over the sensorimotor cortex (Fc3, Fcz, Fc4, C3, Cz, C4, Cp3, Cpz, Cp4) according to the international "Ten–Ten" system.

Our experimental dataset consisted of EEG recordings of 15 subjects, all of them healthy, 18-33, never experienced BCI-based training. During experimental session, participants were sitting in the comfortable chair with the hands lying on the armrests in the relaxed position. Experimental design was to clench the right or left fist after the long or short audio signal, respectively, and hold it for 4-5 seconds until the same second signal. The interval between two tasks (end of the previous task and beginning of the next) was also randomly chosen in the range 6-8 seconds (see fig. 1a for the detailed scheme of the experimental procedure). Experiment lasted approximately 30 minutes and included 30 movements with each hand. Audio commands for two types of movements were presented randomly in order to avoid the adaptation effect.

Before applying the time-frequency analysis, we performed a set of prerocessing steps with obtained data. EEG signal was filtered using 5^{th} order Butterworth band-pass filter in the range 1-100 Hz. Then, whole experimental recording was sliced on 14-seconds trials consisting of 6 seconds of background preceding the audio signal and 8 seconds after the signal.

2.2 Time-frequency analysis

On the next step we used the continuous wavelet transform (CWT), a well-known method widely applied in neuroscience to explore the time-frequency features of the biological signals:

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

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

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

as a complex Morlet wavelet, which is widely used in the analysis of neurophysiological signals.[19] Here, $i = \sqrt{-1}$ and $\omega_0 = 2\pi$ is the central frequency of the Morlet wavelet.[20]

Then, obtained wavelet coefficients were averaged over the μ-rhythm (8-15 Hz):

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

An example of CWT applied to the single-trial EEG, as well as the corresponding spectral power W_μ, is presented on Fig. 1c. Visual inspection shows that ERD in μ-band precedes movement execution. On the next step, we use W_μ time series to analyze motor-related dynamics via RQA.

2.3 Recurrence quantification analysis

The idea of recurrence plots (RP) uses the natural property of many dynamical processes to have periodic behavior. These periodicities, or recurrences, are represented as the neigbouring points of the reconstructed phase space trajectory. To visualize them, we construct binary matrix $R_{i,j}$:

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

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.[21] Therefore, two states of the system x_i an x_j are considered as similar, if they enter each other's ϵ-neighborhood. 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 present paper, we estimate RQA measures in 3-sec floating window (750x750 data points). The first measure is recurrence rate:

$$RR = \frac{1}{N^2} \sum_{i,j=1}^{N} R_{i,j}(\epsilon), \quad (5)$$

which is the basic measure that quantifies the density of recurrence points in the RP.[22]

The next measure is determinism, which quantifies the diagonal structures of RP:

$$DET = \frac{\sum_{l=l_{min}}^{N} l R_{i,j}(\epsilon)}{\sum_{l=1}^{N} l R_{i,j}(\epsilon)}, \quad (6)$$

with $l_{min} = 2$ – minimal considered length of diagonal line. A diagonal line in RP represents the regime when system repeatedly returns to the particular state. Therefore, DET 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.

We also considered laminarity, which is the ratio between the recurrence points from vertical lines to all recurrence points of PR:

$$LAM = \frac{\sum_{v=v_{min}}^{N} v R_{i,j}(\epsilon)}{\sum_{v=1}^{N} v R_{i,j}(\epsilon)}, \quad (7)$$

where $v_{min} = 2$ is a minimal considered length of vertical line. LAM describe the presence of laminar states in the process.

The windowed modification of these three measures allows us to monitor their time dependence and capture transitions from baseline to motor-related pattern. To evaluate the significance of these transitions, we compared two different experimental conditions (motor execution and preceding background) using nonparametric statistical test.

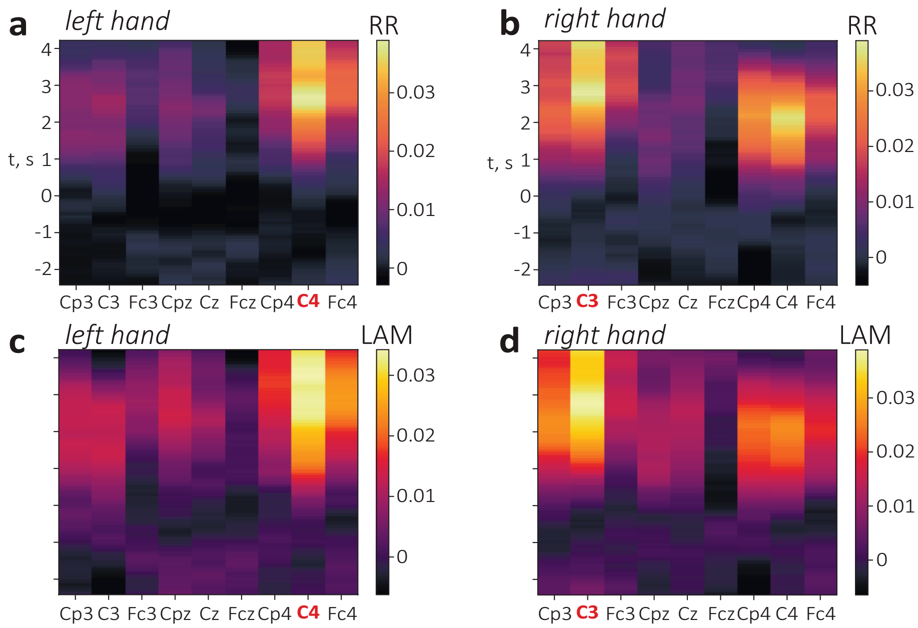

Figure 2. RQA measures time dependencies: (a) RR for left hand; (b) RR right hand averaged over the trials; (c) LAM for left hand; (d) LAM for right hand.

3. RESULTS

On Fig. 1d we see a recurrence plot for the single trial W_μ time series, and Fig. 1c — corresponding RQA measures. We see pronounced changes in the RR and LAM taking place after the audio signal and covering the short period of the motor preparation (according to the EMG, the movement onset was approximately 2 seconds after the signal). Such time dependence of RQA measures quantify the area with higher density on the RP. Increase of RR can be interpreted as the evidence of reduction of signal's complexity. Indeed, motor-related μ-rhythm desynchronization associated with the drop of the amplitude of corresponding EEG oscillations naturally causes increase of repeating states, since the signal becomes less uncorrelated, which is reflected as neigbouring trajectories in the phase space.

Next, we demonstrate that such features are valid for all trials. On fig. 2 we show RR and LAM averaged over the trials for all considered channels. Here we see clear separation of significant changes on different hemispheres. Moreover, we see that motor execution with right and left hands cause pronounced RR and LAM increase in the opposite hemispheres. Despite the fact that changes of RR for right hand are pronounced in both left and right hemispheres (see 2b), in the right hemisphere RR drops shortly after the peak unlike in the right hemisphere. These observations are consistent with the well-known concept of contralaterality of motor-related brain activity.

Note that both LAM and RR have the most pronounced peak in channels C3 and C4 for right and left hand, respectively. Indeed, these channels are known to be most informative in motor-related EEG studies.[23–25] We select these two channels to calculate LAM time dependence for right and left hand in different hemispheres (see Fig. 3).

We see that the contralaterality of RQA measures is valid for the group of subjects. Right hand LAM has the most pronounced peak in the left hemisphere (Fig. 3a) and the less pronounced — in the right (Fig. 3b). Moreover, unlike in the right hemisphere, in C3 LAM increases sharply for both hands. We hypothesize that this observation is caused by the features of experimental dataset consisted of preliminary right-handed subjects.

4. CONCLUSION

In present paper we studied the application of RQA to the spectral power time series of motor-related EEG. We revealed that motor execution is associated with increase of RR and LAM, which evidences of transition from

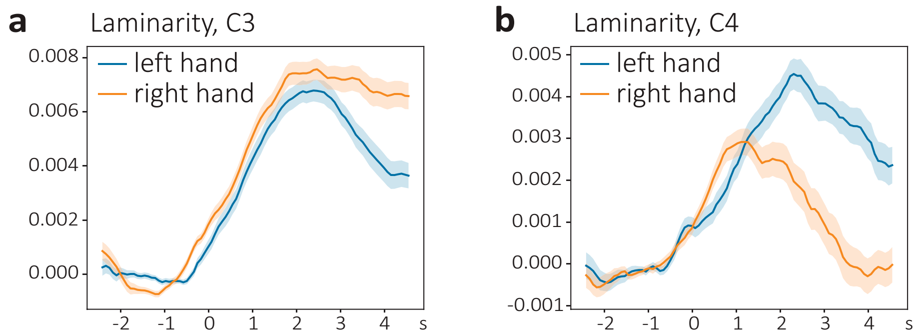

Figure 3. LAM time dependence averaged over the subjects for channels from right and left hemispheres with standard error.

uncorrelated background brain activity to more regular oscillations, which can be considered as ERD in terms of RQA. In our opinion, presented results indicate that RQA is a powerful tool, which has great potential in the development of methods for motor-related activity detection.

5. ACKNOWLEDGMENTS

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