Time-frequency and recurrence quantification analysis detect limb movement execution from EEG data

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***Abstract*— In present paper we consider application of recurrence quantification analysis (RQA) in detection of motor-related electroencephalograms (EEG). Particularly, we apply RQA to reveal transitions of mu-rhythm dynamics extracted from multichannel EEG recorded in motor cortex. The results show that the considering RQA measures of EEG in time-frequency domain one can effectively reveal dynamical features of motor-related brain activity.**

Keywords—EEG, recurrence quantification analysis, recurrence plots, continuous wavelet transform, motor-related brain activity, event-related desynchronization

I. Introduction

Analysis and accurate detection of brain motor-related activity is crucial in neurorehabilitation of post-stroke and disabled patients based on biological feedback [1]. Traditional techniques for motor activity extraction from multivariate magneto- and electroencephalography (M\EEG) include time-frequency and event-related desynchronization analysis, common spatial patterns, spatio-spectral decomposition and machine learning [2-6]. This problem is of strong demand and development of new methods of identification of motor-related EEG pattern is essential for effective therapy. In present paper we investigate the application of recurrence quantification analysis (RQA), recently used in inference of financial and climatic changes from data [7], to detect transitions of brain behavior induced by motor executions.

Recurrent behavior is a fundamental property of many dynamical systems of different nature, which can be used to distinct its different states and track its evolution in time. First discussed by Poincaré, recurrences are now studied in various areas of research. In particular, one of the well-known methods is recurrence plots (RP), which is widely used in astrophysics [8,9], physiology [10], climate research [11] and other areas, allowing to detect and visualize the repeating temporal states in nonlinear and non-stationary data. However, there is a lack of systematic studies of the biological and neurophysiological signals in terms of recurrence analysis. RQA has been predominantly used for analysis of well-pronounced patterns, such as epileptic seizures, wakefulness or sleep stages and event-related potentials during attention tasks [12-15].

However, the motor action causes less reproducible pattern on EEG highly dependent on individual characteristics of participants. With this goal in mind, we propose an approach based on combination of time-frequency and recurrence quantification analysis. RQA provides quantitative interpretations of various structures observed in RPs. By applying RQA measures to the mu-rhythm (8-13 Hz) energy time-series extracted via wavelet transform, we reveal the event-related desynchronization (ERD) in motor cortex, which is a well-known hallmark of motor-related brain activity. We show that RQA measures are highly sensitive to the start of limb movement execution.

II. Materials and Methods

A. Experimental data

During the experimental session subjects sat in a comfortable chair with their hands relaxingly lying on the table and squeezed their hand into fists on the audio command. We used long (1 sec) and short (0.5 sec) signals as a command to execute movement with left and right hand, respectively. Subjects were instructed to squeeze hands after the first signal and hold it until the second one (approximately 4-5 sec). Electrical brain activity was recorded by "Encephalan-EEGR-19/26" (Medicom MTD company, Taganrog, Russian Federation) using 10-10 international EEG scheme. For further analysis we used only recordings from motor cortex sensors (Cp3, Cp4, Cpz, C3, C4, Cz, Fc3, Fc4, Fcz). In order to match brain activity EEG data with motor execution, we also recorded electromyograms (EMG) on both hands.

B. Continuous wavelet transform

At the first step, we applied CWT to the 14 sec trials, each corresponding to a single movement. Wavelet coefficients were calculated as follows:

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

with Morlet wavelet as a mother wavelet function φ.

Since we were focused on the motor-related brain activity, we calculated wavelet coefficients averaged over the mu-rhythm (8-13 Hz), which contains valuable information about EEG motor-related dynamics:

$$W_\mu(t) = \int_{f\epsilon f_\mu} W(f,t)df \qquad (2)$$

Obtained time series were used on the next step for RQA measures evaluation.

C. Recurrence quantification analysis

By definition recurrence plot evaluates recurrences of the phase space trajectory of the dynamical system by considering the ε-neighborhood of the current state. Thus, we construct binary recurrence matrix R with ε=2 as follows:

$$R_{i,j} = \begin{cases} 0, if\ \varepsilon - \left|\left|\vec{x_i} - \vec{x_j}\right|\right| < 0 \\ 1, \qquad\qquad otherwise \end{cases} \qquad (3)$$

As stated above, RQA allows to quantify the RP by analyzing the structures formed by vertical/horizontal and diagonal lines. In our study we use these three basic measures

– determinism (DET), laminarity (LAM) and recurrence rate RR) – to evaluate the dynamics of mu-rhythm wavelet energy of motor-related EEG.

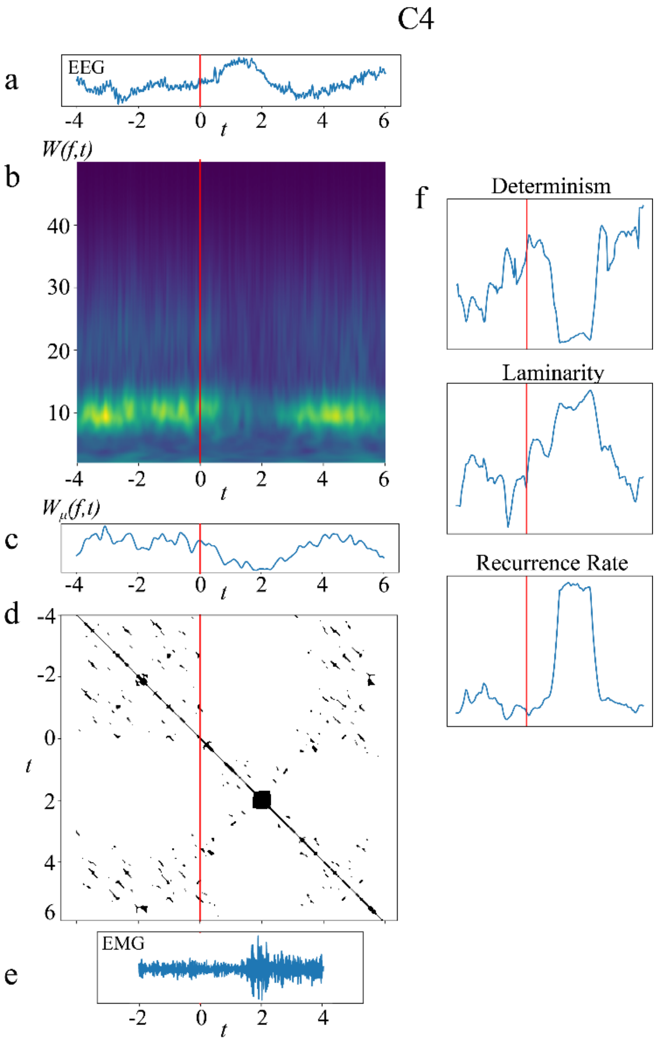

Fig. 1. For all presented plots, t is time, sec, with audio command placed in 0 and marked with red line. (a) Raw EEG signal corresponding to the movement; (b) wavelet surface of corresponding EEG signal; (c) averaged mu-rhythm energy W_μ; (d) recurrence plot of considering time series; (e) matched EMG signal; (f) RQA metrics.

RR estimates the density of recurrence points in RP:

$$RR = \frac{1}{N^2}\sum_{i,j=1}^{N} R_{I,J}(\varepsilon) \quad (4)$$

DET represents a relevant measure of signal complexity and predictability of the process. Determinism is defined as the percentage of recurrence points that form diagonal lines in RP:

$$DET = \frac{\sum_{l=l_{min}}^{N} lP(l)}{\sum_{l=1}^{N} lP(l)} \quad (5)$$

where $l_{min} = 150$ is a minimal considered length of diagonal line.

On the contrary, LAM characterizes laminar or stationary states of considered process and measures the vertical/horizontal lines ratio in RP:

$$LAM = \frac{\sum_{v=v_{min}}^{N} vP(v)}{\sum_{v=1}^{N} vP(v)} \quad (6)$$

where $v_{min} = 20$ is a minimal considered length of vertical/horizontal lines.

III. Results

Fig. 1 represents the results of CWT and RQA for one of the subjects, which has pronounced ERD of mu-rhythm corresponding to the movement execution. We show the results of left-hand movement quantification form EEG signals recorded from C4 sensor. In Fig. 1b,c,e one can see a considerable suppression of mu-rhythm during motor action execution. It is also seen from Fig. 1c, that mu-rhythm behavior preceding the audio command is characterized by the deviations of mu-rhythm oscillatory energy, while more stationary mu-rhythm behavior is peculiar to the motor-execution.

Fig. 1d shows RP constructed from time-series presented in Fig. 1c. One may notice that background activity and motor execution represent two separate blocks in RP. Fig. 1f shows corresponding quantifications of RP with RQA measures of DET, LAM and RR (top-down). Indeed, one can see that chosen measures clearly indicate start of motor-execution associated with short-term depression of mu-rhythm. Decreasing of DET, along with increase of LAM and RR is interpreted as definition of ERD in terms of RQA. A negative dynamics of determinism indicates that the system becomes less correlated and deterministic, which is consistent with the known effects of ERD. Consequently, the density of the recurrent points grows. It is notable that laminarity starts growing slightly before movement onset, which indicated that actual motor activity causes the emergence of laminar states in mu-rhythm energy, including the movement itself and short preceding period, which can also be interpreted as a preparation to the movement.

IV. Conclusion

In present paper we used recurrence quantification analysis to study mu-rhythm dynamics of motor-related EEG.

In general, obtained results are consistent with known facts about motor-related ERD in mu-rhythm. Proposed method is novel in neuroscience, which applications for brain-computer interfaces for rehabilitation is rather poorly studied. However, present paper revealed the ability of RQA to provide a deeper insight into the dynamics of EEG signal associated with motor action, which can be used for detection of motor pattern. We believe that results presented in this study will be useful for fundamental science, as well as for the developers of EEG processing methods for brain-computer interfaces.

Acknowledgment

This work was supported by the President Program (projects NSH-2737.2018.2).

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