Recurrence plot structure of motor-related human EEG

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***Abstract*—In present paper we consider structure of recurrence plot (RP) of human motor-related electroencephalography (EEG) signal recorded in somatosensory cortex and filtered in mu-band (8-13 Hz). We show that in averaged EEG signal background activity is mostly characterized by the diagonal lines, while motor task execution is associated with increase of recurrence points density and the emergence of vertical and horizontal lines. We also demonstrate that these features of RP structure also observed in single EEG trials.**

***Keywords*—EEG, recurrence plots, motor-related brain activity, event-related desynchronization, single-trial analysis**

I. Introduction

Neurorehabilitation of post-stroke and disabled patients based on biological feedback is a demanding technology [1]. Effective application of biological feedback requires advanced methods for precise detection and quantification of motor actions quality based on brain activity signals. Usually, brain motor activity is analyzed from multichannel magneto- and electroencephalography (M\EEG) signals by time-frequency and event-related desynchronization analysis, common spatial patterns, spatio-spectral decomposition and machine learning [2-6]. Many of the existing methods require high computational costs therefore it is hardly possible to use them in real-time applications. This problem is of strong demand and development of new methods of identification of motor-related EEG pattern is essential for effective therapy. In this context, analysis of recurrence properties of EEG signals may provide the efficient tool motor patterns recognition. This study considers features of recurrence plots (RP) structure observed in averaged EEG data as well as in single EEG trials.

Recurrent behavior is a fundamental property of dynamical systems, which can be used to distinguish between different regimes of behavior. First discussed by Poincaré, recurrences are now applied to the analysis of various processes in different areas of science and technology. One of the well-known methods is recurrence plots (RP) reconstruction – a visual representation of system recurrences obtained from nonlinear non-stationary data – which is widely used in finance and climate research [7,8], astrophysics [9,10], physiology [11] etc. In context of neuroscience, Refs. [12,13] show that RPs are quite useful in identification of N100 and P300 event-related potentials (ERPs). Based on these results, we conclude that recurrence analysis might be extremely helpful in identification of motor-related brain activity associated with event-related desynchronization (ERD) of mu-waves (8-13 Hz) in somatosensory cortex.

With this goal in mind, we consider features of RP structure of EEG segments recorded in somatosensory cortex and related with motor executions. We demonstrate, that motor actions are accompanied by recurrence points density increase and emergence of vertical and horizontal lines, while pre-motor activity is characterized mostly by diagonal lines in RP.

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) with 250 Hz sampling rate 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. Filtering and segmentation

After signals acquisition, EEG data was preliminary filtered by th 5^{th} order band-pass Butterworths filter with lower and higher cut-off frequencies of 8 and 13 Hz respectively, which corresponds to the boundaries of mu-frequency band. EMG signals were filtered with band-pass Butterworth filter with lower and higher cut-off frequencies of 10 and 70 Hz respectively. Filtered EMG signal shows high-frequency electrical signal fluctuations associated with muscle tension during the movement execution.

Filtered multichannel EEG recordings were further cut into EEG segments in accordance with experimental protocol. In these segments time moment 0 corresponds to movement command. Also, each segment contains 2 seconds of pre-motor baseline and 6 seconds of motor-related brain activity signal after command.

Along with single trials we considered EEG segments averaged over trials, representing most pronounced motor related ERDs.

C. Recurrence quantification analysis

Recurrence plot evaluates recurrences of the phase space trajectory of the dynamical system by considering the ε-neighborhood of the current state. For each segment we reconstructed phase trajectory with embedding parameters: d=4 and T=0.03 sec.

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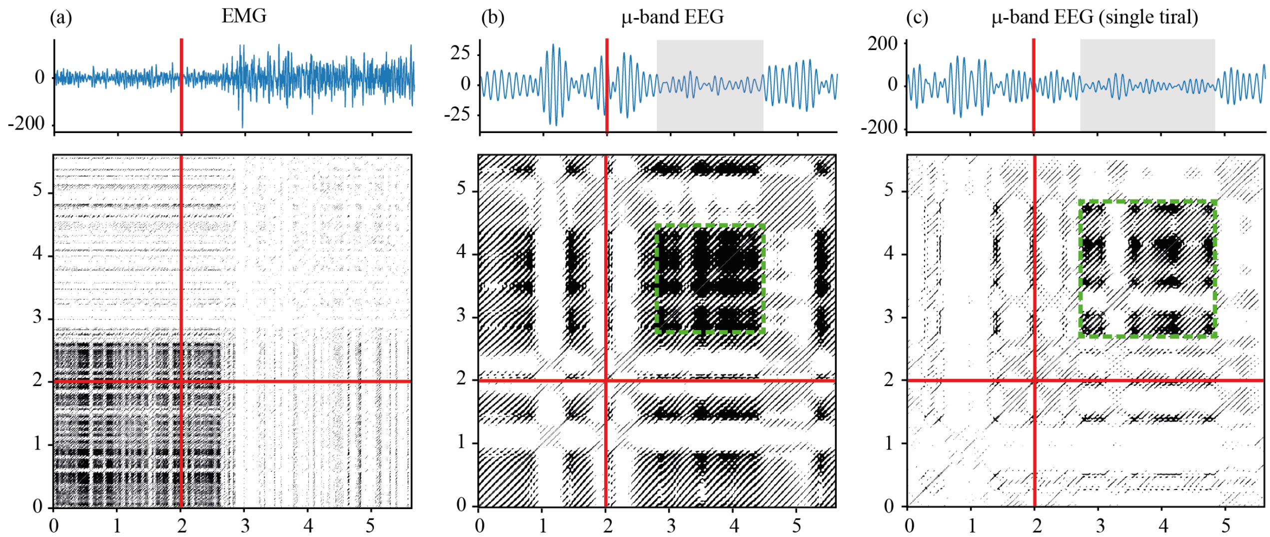

Fig. 1. Upper row represents signals of averaged filtered EMG (a), averaged mu-band filtered EEG recorded from C4 sensor (b), single mu-band filtered EEG recorded from C4 sensor (c). Lower row illustrates correspoding RP structures. Horizontal and vertiacal bold red line indicates start of the audio command, grey areas in (b,c) upper row highlight motor-related ERD, green dashed line squares in lower rows of (b,c) show RP structures associated with ERD.

Here, d is an embedding dimension and T is an embedding delay. The parameters were defined using standard methods for phase trajectory reconstruction: false nearest neighbors and mutual information.

Thus, we construct binary recurrence matrix R with ε=15 mV as follows:

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

where x – is a reconstructed phase trajectory of original EEG signal segment.

III. Results

Fig. 1 represents the results of RP reconstruction of EMG and EEG data recorded during motor task accomplishment. Averaged filtered EMG shows start of movement execution approximately 1 sec after audio command (Fig. 1,a). It is also seen from corresponding RP, that recurrence properties of EMG signal during movement execution differ from the background – the recurrence matrix becomes sparse, which is an indicator of noisy dynamics. Note, that properties of motor-related RP block of EMG signal (1-6 sec after command) do not change in time. At the same time, RP analysis of motor-related averaged EEG trials recorded from C4 sensor in somatosensory cortex clearly indicate change of brain dynamics associated mu-rhythm suppression (ERD). It's important, that analysis of brain activity, allows direct identification of the squeezing action, which is not seen from muscle signal. One may observe, that motor-related area of RP reconstructed from averaged EEG signal has a few pronounced properties: increased recurrence points density and emergence of vertical and horizontal lines. These features of RP structure are referenced to as holding a phase point in a small volume of embedded phase space. In terms of considered EEG signal, mentioned RP properties clearly indicate suppression of mu-oscillations in somatosensory cortex, which emerges during motor task execution. Described RP features found during analysis of averaged EEG segment are observed even in single trials of motor-related EEGs (see Fig. 1,c). RPs of single EEG trial also contain a well-defined block with similar properties as observed in averaged EEG signal and allowing clear detection of motor-related ERD in mu-band.

IV. Conclusion

In present paper we used recurrence plots structure analysis to detect changes in motor-related EEG and EMG segments. While EMG analysis shown differences between hand movements and resting state, RP reconstruction of EEG activity in somatosensory cortex provides direct identification of motor execution. We observed, that RP of averaged EEG signal contains well-defined block associated with ERD in mu-band and characterized by increase of recurrence points density and emergence of vertical and horizontal lines. Interestingly, such properties of RP are observed even in single trials, which may clearly define the region of motor-related task accomplishment.

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 [14].

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