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Recurrence quantification analysis detects P300 on single-trial EEG

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***Abstract*—In the present paper, Recurrence Quantification Analysis was applied to detect event-related potential P300 on single-trial EEG. We demonstrated that the emergence of P300 is associated with EEG complexity increase. Besides, the RQA measure of complexity based on recurrence times quantification is sensitive enough to detect these changes on single-trial EEG.**

***Index Terms*—Recurrence quantification analysis, event-related potential, P300, EEG**

I. Introduction

Recurrence quantification analysis (RQA) is a powerful tool for studying the behavioral characteristics of dynamical systems. Designed for time series analysis, RQA has been popularly applied in climate research [1], in the natural sciences [2], and medicine [3]. Recently, there has been a growing trend to use RQA to analyze the complexity of biological signals. In particular, detecting transitions between different dynamic modes in biological signals via RQA indicates normal responses to external stimuli and pathological conditions.

RQA can successfully detect variability in heart rate [4], arrhythmia [5], and tachycardia [6] using an ECG signal. In addition, RQA is successfully used to analyze signals of a neurophysiological nature. For example, the analysis of the complexity of the EEG signal makes it possible to detect epileptic activity [7] and functional characteristics of brain activity in neurophysiological diseases [8]. Also, the RQA complexity measures made it possible to determine the beginning of hand movement and separate two types of motor action based on the well-known property of contralaterality of motor activity [9].

Within the framework of this work, we apply RQA to detect the P300 potential occurring on the EEG after an audio stimulus on the single-trial EEG. Potential P300 arises as a subject's response to a stimulus and is a positive deviation of the EEG signal voltage, which occurs approximately 300 ms after the presentation of the stimulus [10]. The P300 potential is one of the most widely used markers for brain-computer interfaces [11]. The properties of the P300 can potential vary under the factors of age [12], [13], neurophysiological characteristics [14], and neurodegenerative diseases [15].

As a rule, detection of P300 occurs on averaged EEG time series. Such an assessment is not always practical due to a significant spread of P300 in time on both between- and within-subject levels [16], [17]. In addition, the use of P300 in brain-computer interfaces requires the development of new methods to EEG analysis that are sensitive enough to detect effects in single trials.

In this work, we propose an estimate of the EEG signals complexity using RQA measures for the single-trial detection of P300. RQA measures are a quantitative assessment of various structures on recurrence plots, which is a visualization of the fundamental property of dynamical systems to repeat their states over time.

In this work, we propose an estimate of the EEG signals complexity using RQA measures for the single-trial detection of P300. RQA measures are a quantitative assessment of various structures on recurrence plots, which is a visualization of the fundamental property of dynamical systems to repeat their states over time. We demonstrate that the local increase of entropy-based RQA measure indicates the presence of P300. We show that detecting ERP using RQA measures of complexity is a promising approach for potential brain-computer interface applications.

II. Methods

A. EEG dataset

We performed a single-session sensorimotor integration training with 13 volunteers (25.5 $\pm$ 5.3 y.o.). Subjects performed one of the two types of motor activity depending on the audio command:

1) short beep (250 ms) – clench left hand into a fist;
2) long beep (500 ms) – clench right hand into a fist.

The first audio command was followed by the second of the same duration, which was a cue to relax the corresponding hand. The timing of each epoch was chosen randomly in the interval [4,5] sec, and the pause between epochs was [6,8] sec.

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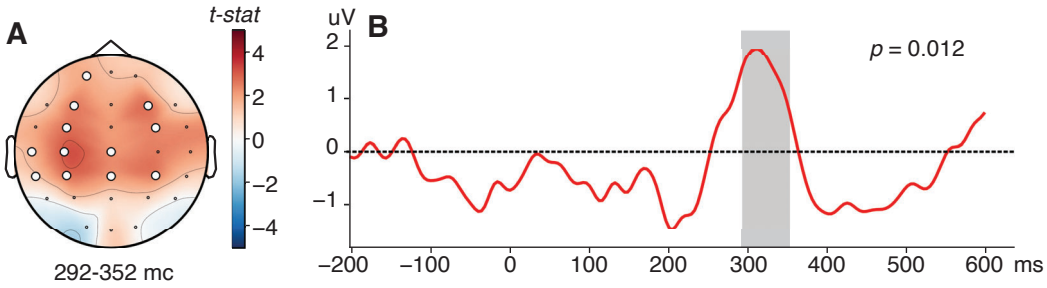

Fig. 1. Sensor-level spatio-temporal cluster analysis of poststimulus EEG. **A** – map of the time-averaged t-statistic for the obtained cluster. White points indicate EEG sensors comprising these clusters. **B** – sensor-averaged EEG time series. Shading highlights the time interval within which the significant within-group differences are observed.

Subjects were seated in a comfortable chair with hands placed on the armrest to avoid non-task-related muscle tension. Each subject performed $N = 30$ movements with each hand.

We used EEG-amplifier "Encephalan EEGR-19/26" (Taganrog, Russia) that records EEG signals sampled on 250 Hz using an extended EEG-sensor placement system "10-20". We applied Notch filter to remove 50 Hz frequency component. Additionally, ocular and muscular artifacts were removed using the independent component analysis, and the final EEG dataset was filtered with a 5^{th} order Butterworth filter in the range of 1-40 Hz.

B. RQA

Using the fundamental property of all dynamical systems to recur, we can determine the recurrence matrix as:

$$R_{i,j} = \Theta(\epsilon - ||x_i - x_j||), i, j = 1, ..., N, \qquad (1)$$

where N is a number of considered states x_i, ϵ is a recurrence threshold, $||\cdot||$ is a Euclidian norm, and Θ is a Heaviside function. Recurrence plot (RP) is a visualization of the recurrence matrix consisting of "white" (non-recurrent) and "black" (recurrent) points. Both recurrent and non-recurrent points form structures, such as vertical/horizontal and diagonal lines. RQA measures reveal the complexity features of considered time series via quantification of these structures. In the present research, we used measures of determinism (DET) and recurrence time entropy (RTE).

Determinism provides an assessment of "black" diagonal lines. A diagonal line means that two segments of trajectory were in each others' neighborhood for a time equal to the length of the line:

$$DET = \frac{\sum_{l=l_{min}}^{N} lP(l)}{\sum_{l=1}^{N} lP(l)} \qquad (2)$$

where $l_{min} = 2$ is a length of the shortest considered line. The high DET of the time series indicates that the system is regular and less complex.

"White" vertical lines are also the essential structures that visualize the recurrent times, i.e., the time that the system requires to repeat its' previous state. These structures can be quantified with the RTE measure:

$$RTE = -\frac{1}{\ln T_{max}} \sum_{t_w 1}^{T_{max}} p(t_w) \ln p(t_w) \in [0, 1], \qquad (3)$$

Here, T_{max} is a maximum recurrence time, $p(t_w)$ is a probability to find a "white" line of exact length t_w. RTE is often used to detect transitions of the systems' behavior from chaotic to periodic and *vice versa*. We performed RQA of EEG time-series in the floating window 50 dp wide (200 ms) and with the step of 2 dp (8 ms).

III. Results

At the first step, we localized the area of significant brain activity associated with P300. Fig. 1 demonstrates the results of the spatio-temporal cluster-based permutation test ($t_{critical} = 3.05$, $p_{pairwise} = 0.005$). The test revealed a significant cluster consisting of 12 sensors in the left motor and temporal lobes with the shift to the right motor lobe (see Fig. 1A). At the same time, the test highlighted the significant time interval 292-352 ms, which is consistent with the traditional ideas of P300 localization (see Fig. 1B).

Next, we performed RQA of the EEG time series. Fig. 2A demonstrates the obtained time dependencies of considered RQA measures averaged over the significant cluster from Fig.1A. Note that the time dependence of ΔRTE has a local maximum in the time interval 152-452 ms, which covers the time when P300 is expected. On the other hand, ΔDET demonstrated a significant increase after 352 ms. In our previous research, we revealed the link between DET increase and motor execution [9]. However, the results indicate that the measure based on the recurrent points is relatively insensitive for the proper detection of ERPs.

On the contrary, the ΔRTE measure based on the "white" lines indicates the link between P300 with a localized burst in the complexity of the EEG signal in the corresponding time

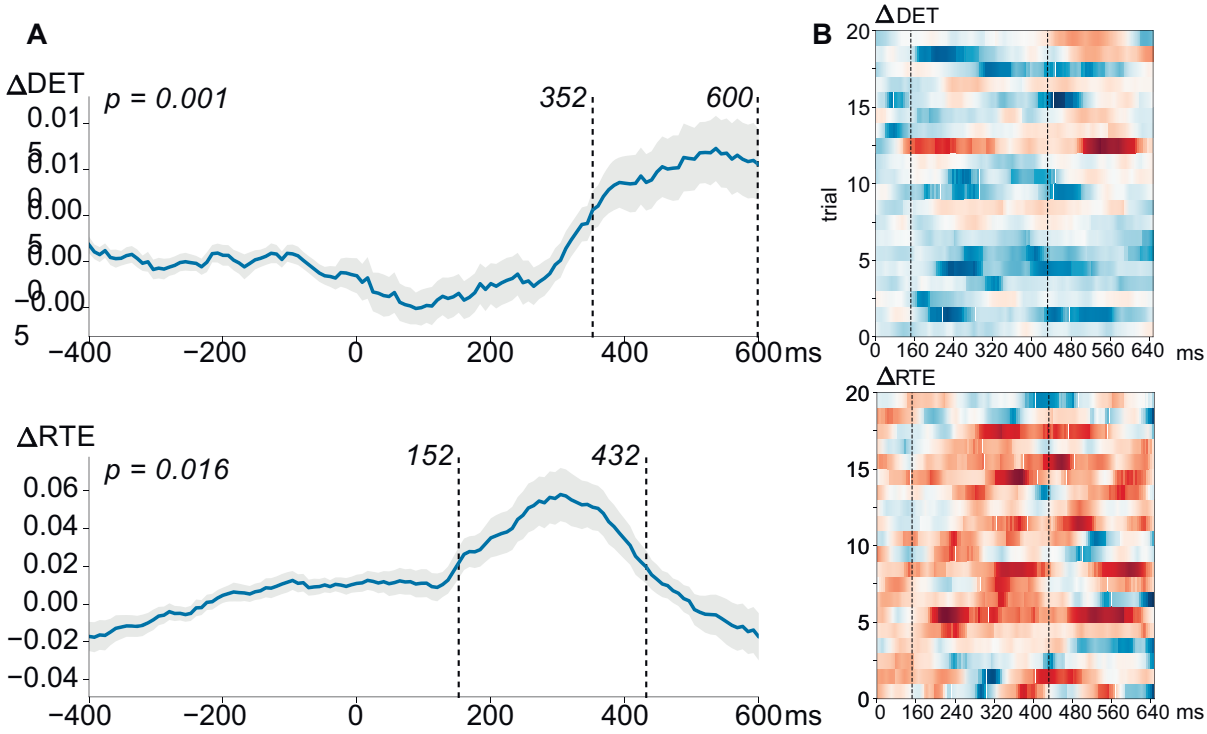

Fig. 2. **A** – time dependencies of RQA measures averaged over a group of subjects. Time series are presented with standard deviation (gray semi-transparent area). The dotted lines mark the time intervals with the most significant deviations of the measures from the zero level. **B** – RQA of the single-trial EEG corresponding to the P300 potential. The trials are averaged over the significant cluster from Fig.1A. The dotted lines indicate the time interval 152-432 ms, which corresponds to the area of significant deviation of the RTE measure from the zero level.

interval. An increase in the number of long "white" lines, meaning an increase in recurrent times, indicates the transition of the EEG signal to a more complex, less regular state.

The presence of a statistically significant time interval on the ΔRTE measure indicates the reproducibility of this effect in the group of subjects. Fig. 2B illustrates the P300 ERP detection on the single-trial EEG averaged over the significant cluster identified at the previous stage. While the ΔDET measure does not show any significant effect associated with ERPs, the ΔRTE measure has a pronounced peak, which fits into the previously identified range of 152-452 ms for each trial. This result indicates that the RTE measure is capable to detect even such subtle characteristics of the brain electrical activity as ERP P300, occurring on the single-trial EEG.

A. Conclusions

In the present paper, we proposed an approach to detect P300 potentials on single-trial EEG via RQA measures of complexity. We demonstrated that the RTE quantifier based on the recurrence times is sensitive to the changes of EEG signals complexity associated with stimulus perception. Our results indicate that RQA is a promising method for possible BCI applications.

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