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Recurrence quantification analysis detects P300 in single-trial EEG

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ABSTRACT

Recurrence quantification analysis was applied to detect the P300 potential on single-trial EEG. We demonstrated that the emergence of P300 as a result of a response to a stimulus is associated with the brain activity complexity increase. The measures of recurrence quantification analysis have sufficient sensitivity to detect these changes even on the single time series.

Keywords: Recurrence quantification analysis, event-related potential, P300, EEG

1. INTRODUCTION

Event-related potential (ERP) is a natural electrophysiological response of the brain to external stimulation or environmental changes, which manifests itself as a characteristic waveform of electrical activity of the cerebral cortex, recorded using electroencephalography (EEG).[1] Usually, it is most pronounced on EEG sensors covering the temporal, prefrontal and somatosensory regions of the cerebral cortex. It is associated with short-term low-frequency modulation of the dynamics of local neuronal populations.[2]

On the one hand, ERP reflects the properties of neuronal processing and working memory and, therefore, is one of the widely used methods in fundamental research to test the functioning of the brain under various experimental conditions.[3,4] On the other hand, being an integral attribute of the brain's response to external stimuli, ERP is widely used as a source of feedback in brain-computer interfaces for rehabilitation and communication with patients whose motor functions are limited or completely lost.

Single EEG trials contain several simultaneously measured processes of neural activity.[5] Traditionally, averaging is applied over a sufficient number of tests to separate the problem-related components of the ERP from the random voltage fluctuations. Identifying ERPs from a small amount of electrophysiological data is a complex task in which nonlinear data analysis tools can be useful for example for brain-computer interfaces.[6]

In the early works of Marwan et al., the effectiveness of recurrence quantification analysis (RQA) of time series in distinguishing ERP components was demonstrated.[7–9] To this end, they used a measure of laminarity based on the assessment of vertical lines to quantify the P300 and N400 components. In this paper, we apply a more advanced quantitative measure of signal complexity based on the distribution of the recurrence time, namely the recurrence time entropy, RTE,[10] to solve the problem of detecting the P300 component. This complexity measure is excellent for analyzing changes in the characteristics of non-stationary processes and transitions from regular dynamics to chaos in model deterministic systems.[11] It has also proven itself well in solving the problem of identifying a pattern of motor and perceptual activity from EEG signals.[12–14]

Detection of the P300 potential is carried out during the sensorimotor integration training session with repeated stimulation of the subjects with short sound signals. Based on the analysis of a multichannel EEG covering the entire surface of the cerebral cortex, we show that a local increase in the RTE complexity measure in physiologically significant EEG sensors indicates the presence of the P300 component. We expect that, due to the properties of the signal to which the RTE measure is sensitive, this quantitative indicator has prospects for identifying ERPs from individual segments of EEG signals.

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2. METHODS

2.1 Experimental design

The EEG data set was recorded during an experimental session on sensorimotor integration training, during which the subjects were instructed to perform hand movements after sound signals. In this case, a short sound signal (250 ms) was a command for movement with the left hand, a long sound signal (500 ms) – with the right hand. During the experiment, the subjects sat in a comfortable chair, placing their hands on the table in front of them in a relaxed position in order to avoid unrelated muscle activity. Each subject made 30 movements with each hand, for a total of $N = 60$ movements. The experimental session lasted about 10 minutes for each subject.

In total, 13 volunteers at the age of 25.5 ± 5.3 years took part in the experiments. Each participant signed an informed consent to conduct the experiment. The design of the experimental study was approved by the Ethics Commission of the Innopolis University and was carried out in accordance with the Declaration of Helsinki.

EEG signals were recorded using an amplifier Encephalan EEGR-19/26 (Medikom MTD, Taganrog, Russia) with a sampling rate of 250 Hz. An extended 10-20 scheme of 32 sensors was used for recording. A notch filter with a cutoff frequency of 50 Hz was applied to the recorded signals. Also, EEG signals were cleaned from oculomotor and cardio artifacts using the independent component analysis and filtered in the range of 1-40 Hz with a 5th order Butterworth filter.

After preprocessing, a set of 30 EEG signal segments (trials) with a duration of 1.5 seconds was obtained for each subject, including 500 ms before and 1000 ms after a short sound signal. After visual inspection, trials with artifacts that could not be removed at the preprocessing stage were excluded from the final sample (10 trials for each subject).

2.2 Recurrence quantification analysis

RQA measures allow estimating the complexity of time series based on quantitative analysis of recurrent states. Using the fundamental property of dynamical systems to repeat their states in time, or the property of recurrence, we can define a recurrent matrix:

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

where N is the number of considered states of the reconstructed phase trajectory, ϵ is the recurrent threshold, which is the size of the region, the states into which are considered recurrent, $||\cdot||$ is the norm and Θ is the Heaviside function. The choice of ϵ is one of the most important aspects of RQA, since the size of the area for searching for recurrent states determines the recurrence plot appearance and, accordingly, the results of its quantitative analysis. In this study, the approach proposed in[11] was used, according to which the value was chosen as the 3rd percentile of the distribution of the distance matrix.

Recurrence plot is a visualization of a binary matrix consisting of "black" (recurrent) and "white" (non-recurrent) points. Both "black" and "white" dots form structures, the quantitative analysis of which makes it possible to assess the characteristics of the signal complexity. In this work, we applied measures of determinism (DET), laminarity (LAM) and recurrence time entropy (RTE).

DET measures the black diagonal lines on recurrence plot:

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

where l_{min} is the minimum considered length of the diagonal line. A diagonal line in the recurrence plot means that two segments of the phase trajectory were in the vicinity of each other for a time equal to the length of the line. Thus, a high DET measure indicates a more regular and less complex process.

Black vertical lines are estimated by the LAM measure and characterize the time interval during which the state of the system did not change or changed very slowly:

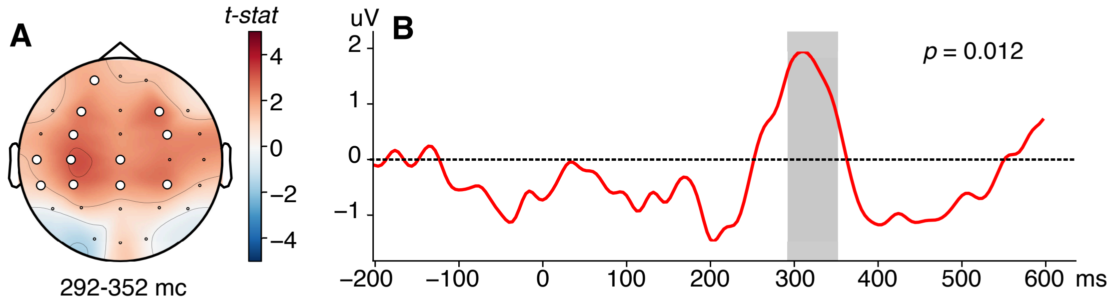

Figure 1. Spatio-temporal cluster test of EEG data corresponding to post-stimulus activity in a group of subjects. **A** – t-statistics for EEG sensors. EEG sensors included in a significant cluster are marked with white circles. **B** – EEG time series averaged over a significant cluster. The time interval in which the deviations of activity from the zero level are the most significant are highlighted in gray.

$$LAM = \frac{\sum_{v=v_{min}}^{N} vP(v)}{\sum_{v=1}^{N} vP(v)} \tag{3}$$

Besides, in the context of RQA, an important characteristic of the process is the recurrence time or time interval required to return the phase trajectory to the vicinity of the previously visited state. It is possible to estimate the recurrence time on the recurrence plot using the vertical (horizontal) white lines:

$$RTE = -\frac{1}{\ln T_{max}} \sum_{t_w=1}^{T_{max}} p(t_w) \ln p(t_w) \in [0, 1] \tag{4}$$

where T_{max} is the greatest recurrent time, $p(t_w)$ is the probability of meeting a white vertical line of the exact length t_w on a recurrence plot. The RTE measure characterizes the transitions of the system from a chaotic to an periodic state and *vice versa*.

RQA of the EEG time series was carried out in a floating window with a width of 50 points (200 ms) and a step of 2 points (8 ms). All measures were baseline-corrected.

2.3 Statistical analysis

The significance of the presented results was confirmed using cluster-based statistical tests based on random permutations. For statistical analysis at the sensory level, a spatio-temporal cluster statistical test was used.[15]

3. RESULTS

Fig. 1 shows the result of the spatio-temporal cluster test of the obtained dataset ($t_{critical}$= 3.05, $p_{pairwise}$ = 0.005). Fig. 1A shows that the area of significant changes is concentrated in the region of the left motor and temporal regions with a transition to the right motor region. At the same time, the cluster test identified a significant time interval of 292-352 ms, which corresponds to the localization of ERP P300 (see Fig. 1B).

Next, we performed recurrence quantification analysis of the EEG time series in the group of subjects (see Fig. 2). Note that the time dependence of ΔRTE has a peak in the interval 152-452 ms, which covers the interval of localization of the P300 potential, while the ΔLAM andΔDET measures have a peak of significance after 384 ms and 352 ms, respectively. Earlier, an increase in the ΔDET measure was associated with the occurrence of event-related desynchronization of the mu-rhythm during motor action with upper limbs [15]. However, it can be seen that measures based on "black" points do not have sufficient sensitivity for the analysis of the ERP.

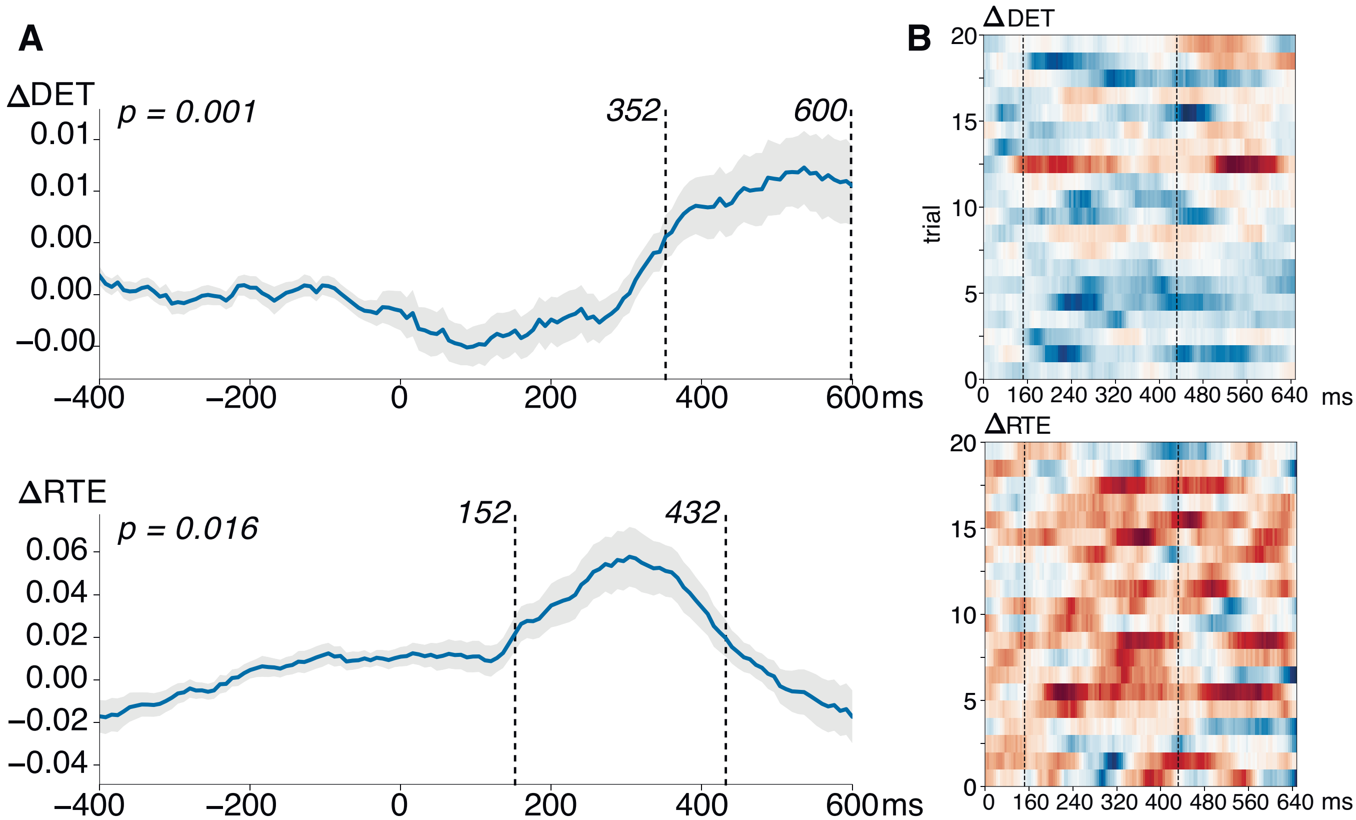

Figure 2. Time dependencies of RQA measures averaged over a group of people presented with standard deviation (gray semi-transparent area). The dotted lines mark the time intervals with the most significant deviations of the values of the measures from the zero level.

On the contrary, the ΔRTE measure based on the "white" lines indicates the link between the P300 and a localized complexity increase of the EEG signal in the corresponding time interval. An increase in the number of long "white" lines, indicating an increase in recurrence times, indicates the transition of the EEG signal to a more complex, less often repetitive 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. 3 illustrates the detection of P300 on the single-trial EEG with averaging over the significant cluster identified at the previous stage. While the ΔLAM and ΔDET measures do not show a significant result when detecting ERPs for individual trials, the ΔRTE measure has a pronounced peak, which for each trial fits into the previously allocated range of 152–452 ms. This result indicates that the ΔRTE measure is able to successfully detect even subtle characteristics of the electrical activity of the brain associated with P300, which appear on the single-trial EEG.

4. CONCLUSION

In this work, an approach to the detection of P300 potentials was proposed based on a recurrence quantification analysis of the complexity of EEG signals recorded during sensorimotor integration training in a group of young healthy subjects. We identified a group of sensors with the most pronounced P300 potential localized in the sensorimotor region with a shift to the left temporal lobe. We demonstrated that a measure of recurrence quantification analysis based on recurrence time, or "white" vertical (or horizontal) lines, is highly sensitive to changes in the complexity characteristics of EEG signals associated with stimulus perception. In particular, the emergence of the P300 is associated with an increase in the number of "white" vertical lines, which characterizes

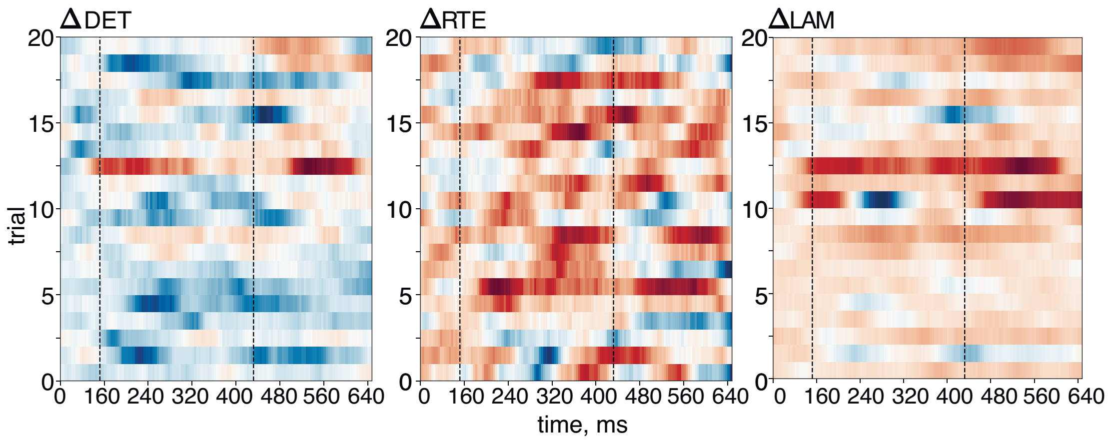

Figure 3. Recurrence quantification analysis of single-trial EEG corresponding to the P300. The trials are averaged over the significant cluster from Fig. 2A. Dashed lines indicate the time interval 152-432 ms, corresponding to the area of significant deviation of the ΔRTE measure from the zero level.

the transition of the electrical activity of the brain from a regular to a more complex, chaotic state. In addition, the RTE measure demonstrated high sensitivity to these changes even on single EEG trials, which is an especially important property in the context of developing systems for detecting and classifying brain activity based on ERP.

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