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ABSTRACT

Authentic recognition of specific patterns of electroencephalograms (EEGs) associated with real and imaginary movements is an important stage for the development of brain-computer interfaces. In experiments with untrained participants, the ability to detect the motor-related brain activity based on the multichannel EEG processing is demonstrated. Using the detrended fluctuation analysis, changes in the EEG patterns during the imagination of hand movements are reported. It is discussed how the ability to recognize brain activity related to motor executions depends on the electrode position.

Keywords: pattern recognition; electroencephalogram; brain-computer interface; detrended fluctuation analysis

1. INTRODUCTION

A recently achieved progress in the creation of brain-computer interfaces (BCIs) offered a new actively developing field of neuroscience and engineering.[1] Despite the idea of BCI has a long-term history,[2,3] a transition from general assumptions to their practical implementation was complicated by the insufficient capabilities of computers and the limitations of existing knowledge in the field of brain physiology. Although the latter limitations are still present, the first steps in the BCIs creation have already led to the appearance of promising devices.

A general idea of the BCI consists in the on-line processing of brain signals that includes recognition of mental actions and their transformation to control commands. In a general sense, BCIs are treated as the devices allowing humans to perform some actions on the surrounding world by using brain signals instead of muscles.[4] Therefore, BCIs provide an alternative to normal output pathways of the brain that include peripheral nerves and muscles. Such alternative transformation of humans mental actions into control commands for hardware allows restoring communication opportunities of disabled people, e.g., humans with disabilities of motor functions.[5–7]

In order to provide recognition of mental actions, multichannel electroencephalograms are often used as the source of information about the brain activity due to the simplicity of acquiring these signals within non-invasive BCIs.[8–10] Complex organization of EEG signals requires application of data processing techniques that could extract information about structural changes in the specific oscillatory patterns occurring during mental actions for their authentic detection and further transformation into the control commands. In our previous study,[11] essential potential of wavelet-based tools[12–14] for this purpose was discussed. In particular, it was established that mental actions influence correlation features of EEG-signals.[11] Taking into account this circumstance, here we characterize correlations in the EEG-data with the detrended fluctuation analysis (DFA)[15,16] being a simpler but powerful method for processing nonstationary time series and short data sets. It allows increasing the speed of processing experimental data, which is especially important for real-time recognition of mental actions within a BCI.

The paper is organized as follows. Section 2 provides a brief description of experimental procedure and the DFA-method used for characterizing power-law correlations in the recorded EEG-signals. In Section 3, we analyze features of EEG-data associated with mental actions and compare correlation properties of the related data with the background electrical activity of the brain. Main concluding remarks are given in Section 4.

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2. MATERIALS AND METHODS

2.1 Experiments

Experiments were performed in accordance with the Helsinki declaration in 12 healthy volunteers (both, males and females) of the ages from 20 to 43. The protocol of the experiments was approved by the local research Ethics Committee of the Saratov State Technical University. EEG signals were acquired with the electroencephalograph Encephalan-EEGR-19/26 ("Medicom-MTD", Taganrog, Russia) using 19 electrodes placed according to the standard setup 10–20 with two reference electrodes. A preliminary data processing was performed with a band pass filter with the cut-off frequencies 1 Hz and 100 Hz, and a 50 Hz notch filter. The sampling rate 250 Hz was used.

Each volunteer was participated in a single experiment of the duration about 30 min. The experimental procedure consisted of 10 sessions among which 5 sessions included real movements of the right hand (RE), and other 5 sessions included imaginary movements (IM) when the volunteer imagines that he/she moves the right hand, with 20 repeated movements (or their imagination) within the session. Before and after the experimental recordings, EEG signals related to a background electrical activity of the brain were acquired during 5 minutes. Each movement was performed after a sound signal, and EEG recordings of the duration 3–4 sec after the sound signal were selected to analyze distinctions from the background brain activity. The RE and IM sessions followed each other, and a short visual instruction appeared at a monitor before sessions. The experiment was carried out in the first half of the day at a specially equipped room where effects of external stimuli such as, e.g., bright light or external noise, were minimized.

2.2 Detrended fluctuation analysis

Analysis of long-range correlations in physiological processes is complicated by at least two main reasons: (i) a nonstationarity of analyzed time series, and (ii) a rapidly decreasing correlation function that does not allow authentic estimation of the scaling exponent quantifying the related power-law dependence. Aiming to avoid these problems, an approach based on a root mean square analysis of a random walk was proposed called as the DFA.[15,16] This method includes a construction of a random walk of the analyzed signal $x(i)$, $i = 1, \dots, N$ as

$$y(k) = \sum_{i=1}^{k} \left[x(i) - \langle x \rangle \right], \tag{1}$$

with $\langle x \rangle$ being the mean value (Fig. 1). The resulting function $y(k)$ represents a random walk and is called as the "profile" of the signal $x(i)$. Further, this profile is divided into parts of equal length n, and a local trend within each part is estimated by a linear or a nonlinear fitting of $y(k)$. In the original paper,[16] a piece-wise linear function $y_n(k)$ was used to describe a local trend, and fluctuations of the detrended time series $[y(k) - y_n(k)]$ were analyzed depending on n

$$F(n) = \sqrt{\frac{1}{N} \sum_{k=1}^{N} \left[y(k) - y_n(k) \right]^2}. \tag{2}$$

After performing these estimations in a wide range of n, a power-law dependence

$$F(n) \sim n^{\alpha} \tag{3}$$

is analyzed, and the scaling exponent α is computed. This exponent allows quantification of correlations in time series $x(i)$. Thus, the values $\alpha < 0.5$ relate to the case of anti-correlations where large and small values of $x(i)$ show an alternation. Larger values ($0.5 < \alpha < 1$) are related to power-law correlations in time series where large values of $x(i)$ more frequently occur after large values and vice versa. When $\alpha > 1$, distinctions from the power-law statistics may occur. It is important to note, that α has a relation to the scaling exponent describing the correlation function and, therefore, the DFA is an alternative to the standard correlation analysis revised for the case of nonstationary data.

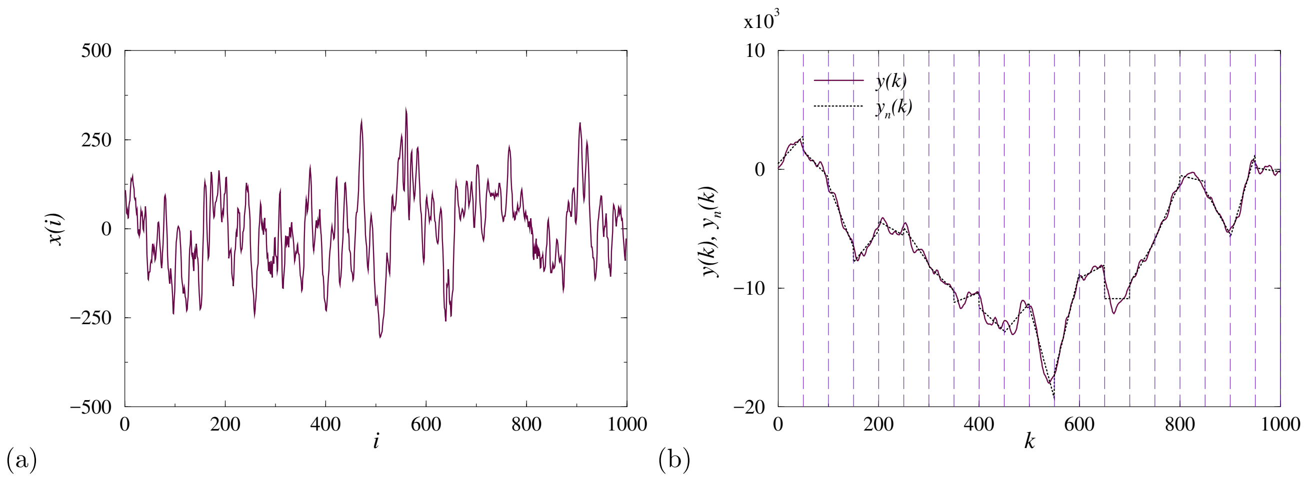

Figure 1. Original time series (a) and the constructed random walk divided into 20 parts with a piece-wise linear function describing a local trend.

3. RESULTS AND DISCUSSION

Because the motor-related brain activity is a short-term process, we performed analysis of relatively small parts of experimental recordings after a sound signal when the hand movement (or its imagination) was started. In Fig. 1 an example of EEG-signal of the duration 4 sec consisting of 1000 samples is shown. The DFA enables analysis of significantly shorter datasets, however, when an asymptotic scaling exponent α is estimated, the case of possible crossover phenomena should be taken into account. In the analysis of physiological time series, "crossover" point in scaling may indicate significant changes of correlation properties between the cases of short-term and long-term correlations.[16]

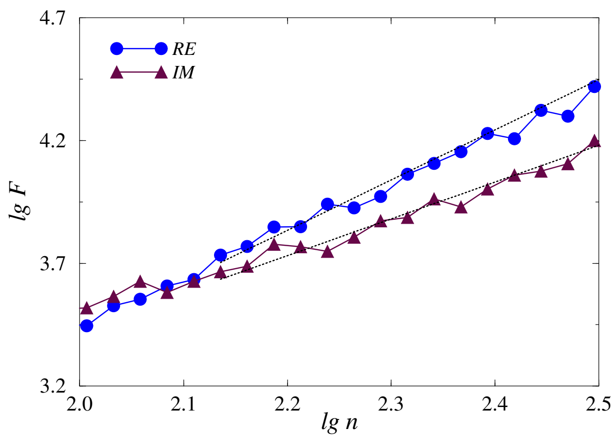

Figure 2. Power-law dependencies $F(n)$ showing distinctions for real and imaginary hand movements.

Figure 2 shows examples of the function (3) in the double-logarithmic plot estimated from EEG-fragments for the case of real and imaginary hand movements of a volunteer. Before performing statistical analysis over all experiments, let us discuss some general features of the given dependence. The slope of the dependence $\log F(\log n)$ is varied depending on the considered scale. In the range of small n (e.g., n <30), distinctions between the cases of real and imaginary hand movements are insignificant, and the value of α estimated in this range of scales may differ from the related value computed for larger n. In general, the case of imaginary movements is characterized by lower values of α, and the given feature is observed not only in the considered example, but also in other experiments.

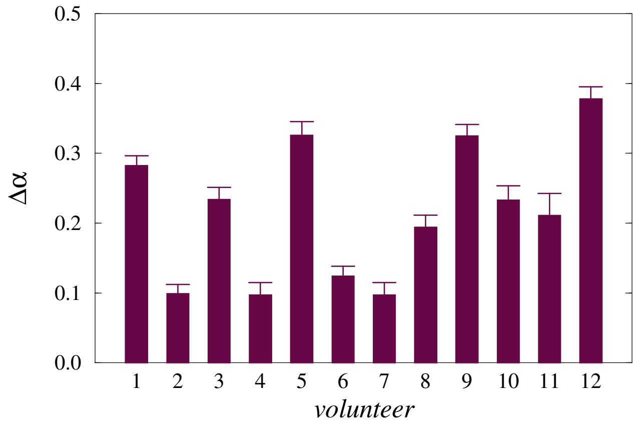

Figure 3. Distinctions between α-values associated with real and imaginary hand movements for all volunteers. Note that the value $\Delta\alpha = \alpha_{RE} - \alpha_{IM}$ is positive in all experiments, and, therefore, there is a similar change in correlation properties. The data are given as mean ± SE.

In order to characterize distinctions between real and imaginary hand movements, we introduced a measure $\Delta\alpha = \alpha_{RE} - \alpha_{IM}$. According to Fig. 3, this measure is positive in all experiments although its value is varied among the subjects. The latter confirms the ability of authentic separation between real and imaginary movements based on correlation features of EEG-data. In Figure 3, averaged values of $\Delta\alpha$ over 5 sessions are shown. The results remain stable under variations in the length of the analyzed data. Thus, similar changes are detected when the analyzed data segment was reduced from 4 sec ($N = 1000$) to 3 sec ($N = 750$). They confirm similar effect that was revealed based on multifractal formalism,[11] but the used DFA-approach is simpler and provides quick computing procedure representing an advantage when developing a software for a brain-computer interface.

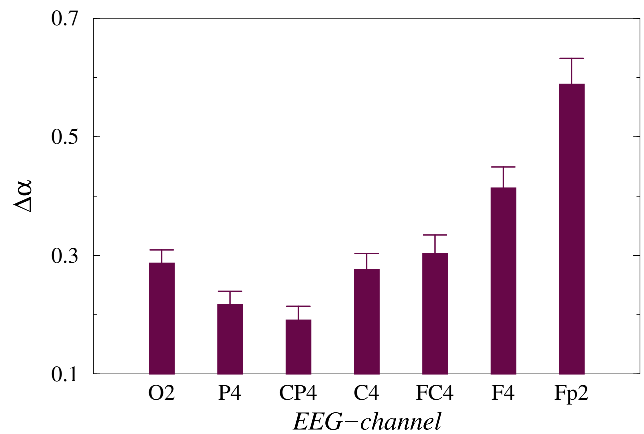

Figure 4. Distinctions between α-values associated with real and imaginary hand movements depending on the electrode position.

Distinctions between real and imaginary hand movements become more pronounced when the recording electrode is selected near the forehead. This is illustrated in Fig. 4 where the electrodes are chosen near a line going from the nape to the forehead. According to this Figure, the difference is 3 times larger when the electrode position changes from the middle part of the head to the forehead. In the region of the occiput, the distinctions are larger than in the middle part but still less expressed as compared with the forehead. When the position of the electrode is varied in the direction from the left side of the head to the right side, no such strong distinctions are observed.

4. CONCLUSION

Identification of EEG-patterns associated with the motor-related brain activity is an important problem whose solution could advance the development of software for signal processing used within BCIs. In this study we performed experiments with untrained volunteers that included sessions of real and imaginary hand movements. The acquired multichannel EEG-signals were analyzed with the DFA-approach that has revealed significant distinctions between the considered types of movements. Moreover, distinctions from the background EEG were also established. Using the detrended fluctuation analysis we have shown that the related distinctions are caused by correlation properties of EEG-data. The quality of detection specific EEG-patterns associated with the motor-related brain activity can be improved by appropriate selection of the electrode position. Stronger distinctions are revealed when the recording electrode is selected near the forehead.

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