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Recognizing Arm Motions by Fluctuation Analysis of EEG Signals

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Abstract—We consider the task of recognition of fragments of multichannel electroencephalogram (EEG) records corresponding to motions of the human arm and to mental representation of these motions. It is shown that the problem of recognition can be solved by processing short EEG segments by the method of fluctuation analysis. The obtained results suggest that fluctuation analysis can be used as an algorithm of the digital signal processing in development of the neurointerface software.

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The problem of constructing brain–computer interfaces (BCIs or neurointerfaces) has a long history, but a breakthrough in this direction has been achieved in the last two decades due to the development of computing technologies and expansion of our knowledge about brain functioning [1–6]. In particular, a noninvasive BCI was proposed for patients with heavy motor disabilities, which allowed them to control the cursor motion on display screen [1]. Other original BCIs provided communication means for totally paralyzed people based on the use of slow cortical potentials for controlling an electronic spelling device [7] and tools for controlling navigation and information intentions of robots [8, 9] based on the analysis of electrooculographic data and electroencephalogram (EEG) records.

On the whole, BCIs are devices that allow people to perform actions in the surrounding world by using brain signals instead of muscular power. These technologies may be required in various fields, including industry, health care, computer systems, etc. Neurointerfaces differ with respect to signal types and methods of their conversion into commands for controlling external actuator devices. Most interesting are BCIs of noninvasive type, which do not require electrodes implanted in the brain. However, these BCIs need using advanced methods of digital signal processing for the recognition of mental intentions.

The main source of information for the development of BCIs is provided by EEG signals, but their analysis and recognition of characteristic features of the electric activity of the brain is still a complicated task [10–15]. The present work was aimed at studying the possibility of recognizing real and imaginary motions of the human arm by using EEG signals capable of providing noninvasive BCIs for various applications.

The experiments were performed in a group of ten healthy volunteers. Multichannel EEGs were recorded using an Encephalan electroencephalograph in the standard 10–20 setting with 19 recording electrodes at 250-Hz sampling rate. Each experiment lasted for 30 min and included tasks of the two types: (i) slowly bend the right arm up at the elbow and (ii) imagine this motion. The onset of arm motion or its mental representation was started by a sound signal, after which the electric brain activity was recorded for 3 s. This time interval included the motion and subsequent short transient process.

The experimental data (EEG records) were processed using the detrended fluctuation analysis (DFA) [16–18] intended for the correlation analysis of nonstationary processes. The DFA procedure involves the following calculations:

1. Construction of a profile of signal $x(k)$, $k = 1, \ldots N$ (one-dimensional random walk):

$$Y(i) = \sum_{k=1}^{i} [x(k) - \langle x \rangle], \quad i = 1, \ldots, N, \tag{1}$$

where $\langle x \rangle$ is the mean signal value.

2. Segmentation of profile $Y(i)$ into M nonoverlapping segments of length n and determination of the local trend $Y_n(i)$ by interpolating $Y(i)$ within each segment. Instead of a piecewise-linear function used in [17], it is possible to use a polynomial approximation.

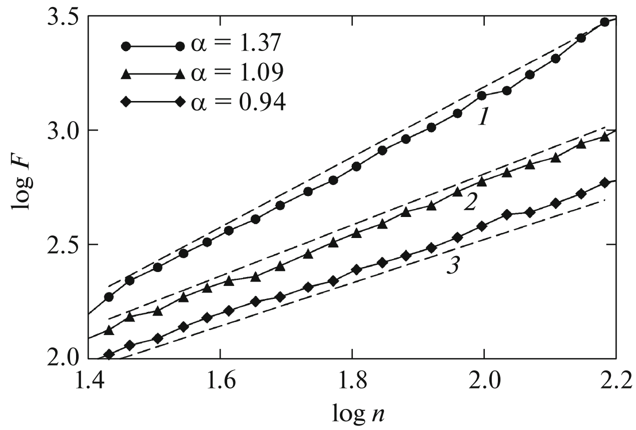

Fig. 1. Difference of scaling exponents α calculated from the slope of log*F* vs. log*n* plots for (*1*) real arm motion, (*2*) imaginary motion, and (*3*) background EEG record.

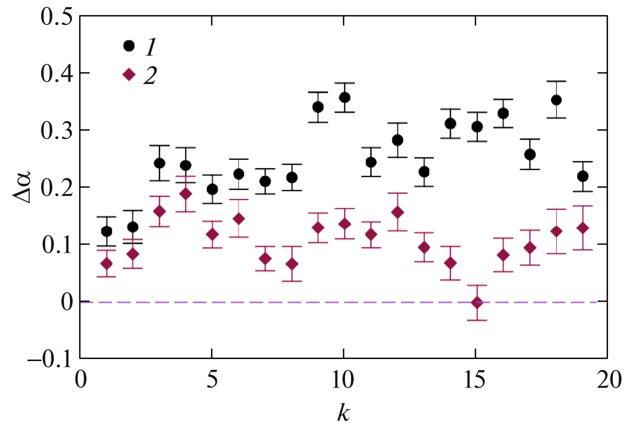

Fig. 2. Difference of calculated scaling exponents α between (*1*) real and imaginary motions and (*2*) between imaginary motions and background EEG activity plotted vs. EEG recording channel number *k*.

3, Subtraction of the local trend and calculation of root-mean-square (rms) fluctuations:

$$F(n) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}[Y(i) - Y_n(i)]^2}. \qquad (2)$$

4. Repetition of calculations for variable segment length n and analysis of the power law relation

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

where α is the DFA scaling exponent. On the double logarithmic scale of log$F$ versus log$n$, this exponent is readily calculated by means of linear approximation. The accuracy of calculations can be additionally improved by segmentation in the forward and reverse directions.

The calculated α values characterize correlations of various types in the experimental data including anticorrelated dynamics ($\alpha < 0.5$ in the presence of alternating large and small values of time series), power-law correlations ($0.5 < \alpha < 1$ for large values more frequently following large ones and small values following small ones), and correlated behavior ($\alpha > 1$) that can differ from the power-law statistics [17]. Stationary processes imply a relationship between exponent α and quantities characterizing the power-law behavior of the correlation function and spectral power density [16].

At the initial stage of investigations, the task of finding reliable differences between real and imaginary motions was solved based on a thorough analysis of experimental data for a single type of motion (slow bending of right arm at the elbow). For this purpose, $F(n)$ data from an arbitrarily selected participant were compared in different states corresponding to real motion, imaginary representation, and background brain activity. Figure 1 shows typical results demonstrating clear differences in slopes within log$n \in [1.4, 2.2]$. Therefore, the states under consideration can be recognized using the DFA method. In order to confirm this, we have carried out statistical analysis of repeated events (100 real motions, 100 imaginary representations, and 100 segments of background activity) for channels of EEG recording. Data presented in Fig. 2 confirm that these states are reliably distinguished. It is important to note that not only the real motions can be distinguished from imaginary, but the imaginary motions can also be distinguished from background EEG pattern—which is even more important for the creation of neurointerfaces. The separation of signals was achieved in almost all channels. However, some channels were present in which the differences were rather weakly pronounced or not reliable. In this respect, it should be emphasized that multichannel EEG recording is necessary for the recognition of motions with increased reliability.

Analysis of the results of investigation for the entire group of volunteers confirmed the above conclusions. According to these results, the separation of real and imaginary motions in all 19 EEG channels was achieved for four participants. For the other four persons, the reliable separation was achieved in 17–18 channels out of 19. There were only two experiments in which the number of channels with weakly pronounced differences reached five (nevertheless, the remaining 14 channels showed reliable differences).

Similarly, we have also sought for differences between the EEG records for imaginary motions and background EEG signals. There was only one participant for which separation of the corresponding EEG fragments was achieved in 7 channels of 19. In all other experiments, the results were much better (from 11 to all 19 reliable distinguished channels) and the results of distinguishing imaginary motions and background activity for four participants were comparable with the results for real motions. A decrease in the number of channels admitting reliable recognition of EEG segments for imaginary motions is probably related to the fact that the experiments were performed with non-pretrained volunteers. The standard practice of work with neurointerfaces consists in conducting experiments after the stage of preliminary learning that provides better concentration of participants. Nevertheless, even the present case demonstrated the possibility of reliably recognizing EEG segments corresponding to mental intentions.

In concluding, the results of our investigation demonstrated the possibility of using the DFA-based correlation analysis for distinguishing real and imaginary motions of human arm with the aid of EEG signal records. This approach is advantageous compared to other methods of digital signal processing such as multifractal analysis [19, 20] used to solve an analogous task previously [21]. The proposed method is characterized by considerably faster response, which allows using it in systems operating online and significantly reducing the delay between decision making and transition from the mental intention to a command controlling actuator devices of the neurointerface.

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