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Detrended fluctuation analysis of EEG patterns associated with real and imaginary arm movements

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HIGHLIGHTS

- Real and imaginary arm movements are recognized with correlation analysis of EEG.
- Mental intentions related to arm movements are detected in the most of EEG- channels.
- DFA can be used as data processing algorithm in brain–computer interfaces.

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ABSTRACT

Based on the detrended fluctuation analysis (DFA), we address the problem of recognizing the electrical activity of the brain associated with movements of the right arm and the imagination of this procedure. In experiments with untrained volunteers, we show the possibility to distinguish between the related EEG patterns. We also demonstrate significant distinctions in the scaling features between background records and EEG signals associated with mental intentions that can be transformed to control commands for brain–computer interfaces. This effect is observed in many EEG channels, although individual features of subjects provided various distributions of brain areas with the most prominent differences.
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1. Introduction

Current achievements in the development of brain–computer interfaces (BCIs) offered a promising area of neuroscience, applied physics and engineering [1,2]. Although the BCI concept has a long history, and the first ideas were discussed about half a century ago [3,4], the path from general hypotheses to their practical implementation was complicated by the inadequate capabilities of the computers and the limitations of existing knowledge about the physiology of the brain. Over the past two decades, various examples of non-invasive BCIs have been proposed that provide real-time recognition of specific patterns of electrical (or magnetic) brain activity associated with mental actions and their transformation to control commands for the hardware of the neurointerfaces [5–10]. In particular, a non-invasive BCI has been created for persons with severe motor impairment to control the movement of the cursor [11], which was based on the adaptive algorithm performing analysis of multichannel electroencephalograms (EEGs). In accordance with such criteria as time and accuracy of movement, the reported results [11] are comparable with invasive BCI. These results show that patients with severe motor dysfunctions can use signals from brain electrical activity to control the neuroprosthesis without implanting electrodes in the brain.

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Other original developments include a communication tool for fully paralyzed patients, which uses the slow cortical potentials of the electroencephalogram to control the electronic spelling device [12]; tools for managing the navigational and informational intentions of the robot based on the analysis of eye movement data and EEG signals [13,14]. Generally speaking, BCIs are devices that allow performing certain actions using brain signals instead of muscles [15–20]. They realize an alternative to normal brain output pathways, which include peripheral nerves and muscles [21–23]. Appropriate technologies are in demand in various fields, including industry, healthcare, computer systems, etc. The current progress in the creation of BCIs is described in the review paper [2], which proposes a classification of BCIs based on such criteria as the source of brain signals, their characteristics and features of functioning. Further elaboration of appropriate technologies, along with the detection of the simplest motor functions, requires recognition of more complex cognitive processes related to fine motor skills, positioning, attention, etc. Recently, functional near-infrared spectroscopy was successfully used to aid in detecting covert awareness in patients who suffer from a disorder of consciousness [24,25]. Application of this tool for BCI development is caused by its low-cost, portability, and enhanced sensitivity to brain activity.

EEG signals also represent the widely used source of information about mental actions, because their record is simple and can be implemented in non-invasive BCI. However, the analysis of these signals and recognition of the specific features of brain electrical activity still presents a challenging problem. Besides the complex organization of EEG data, short duration and strong nonstationarity of the recording fragments related to mental actions create additional difficulties in the data processing. Due to this, the choice of suitable numerical methods is important for the authentic detection of emerging structural changes in EEG. In a recent study [26], we considered the possibilities of wavelet-based multifractal formalism for this purpose and reported distinctions between the correlation properties of EEG signals that occurred in mental actions, compared to the background electrical activity. As a numerical measure we used the mean Hölder exponent. Although these results show an essential potential of wavelet-based tools, the corresponding analysis is rather complicated and has drawbacks in processing speed. From the point of view of the practical implementation of BCI, it is preferable to use numerical methods providing a correlation analysis of short and nonstationary time series that can be applied for real-time analysis of multichannel EEGs. Among such tools, the detrended fluctuation analysis [27–29] was chosen, which seems to be more suitable for the aim of this study. During the last two decades, this tool has allowed to solve many applied problems in diverse research fields [30–37]. Based on DFA, here we study the features of multichannel EEG during mental actions (imagination of arm movements) and provide a comparison with the electrical activity of the brain during real movements and background EEG. We discuss how the recognition results depend on the electrode position.

2. Experiments and methods

2.1. Experiments

All experimental procedures were performed in healthy volunteers (n=10) aged 20 to 43 years, including both men and women. Each volunteer signed an informed medical consent to participate in the experimental work and agreement for further publication. Before the experiment, he/she received all necessary explanations about the process. The protocol of the experiments was approved by the local research ethics committee of the Yuri Gagarin State Technical University of Saratov. The EEGs were recorded with the electroencephalograph "BE Plus LTM"(EB Neuro SPA) which possessed the registration certificate No. FSZ 2011/10629 of 20.09.2011 from the Russian Federation Federal Service of Health Care and Social Development Control. This equipment complies with the following certificates: UNI EN ISO 9001/ISO 9001:2008, EN 46001 ISO 13485:2012, QSR 21 CFR Part 820 Federal Law. A standard setup 10–20 with 19 recording electrodes was used. In the course of the data preprocessing, EEG signals were filtered using a band-pass filter with cut-off frequencies of 1 Hz and 100 Hz, and a 50 Hz notch filter.

Each experiment was conducted for about 30 min and included two types of tasks: the slow right arm lift in the shoulder joint (real arm movement, RAM), and the imagination of this lift (imaginary arm movement, IAM). The movement or its imagination was started by a sound signal, and the electrical activity of the brain was measures for 3 s to analyze distinctions from the background activity of the brain. This time interval was fixed for each event and included the movement itself and the subsequent short transient process. The experimental procedure consisted of 10 sessions: 5 sessions of RAM and 5 sessions of IAM, each of which included 20 repetitive movements (or their imagination). Thus, for each volunteer, 100 records were received for each type of solved tasks. At the beginning and at the end of the experiment, background electrical activity of the brain was acquired within 5 min. The sessions of real and imaginary movements followed one another, and each of them was provided with a preliminary short visual instruction appeared on the monitor. The experiments were conducted in the first half of the day in a specially equipped laboratory where volunteers sat comfortably, and the effects of external stimuli, e.g., noises and bright light, were minimized.

2.2. Data analysis

Characterization of long-range correlations and power-law statistics of physiological time series is complicated by the following reasons: (i) nonstationarity, which limits the applicability of the correlation function, and (ii) a rapid decrease in this function, providing fluctuations of values around zero that are comparable to computational errors. The latter does not allow us to clearly quantify the scaling features of the correlation function in the region of long-range correlations. To avoid such problems, the detrended fluctuation analysis was proposed [27,28], representing a variant of the root mean square analysis of a random walk.

Analysis of a time series $x(i), i = 1, \dots, N$ with DFA is performed in the following steps:

(1) The transition from the initial time series $x(i)$ to the random walk $y(k)$

$$y(k) = \sum_{i=1}^{k} [x(i) - \langle x \rangle], \qquad \langle x \rangle = \frac{1}{N}\sum_{i=1}^{N} x(i). \tag{1}$$

(2) Segmentation of the random walk (or signal profile) $y(k)$ into non-overlapping parts of size n and fitting a local trend $y_n(k)$ within each segment. For this purpose, piece-wise linear functions or polynomials can be applied. Depending on the fitting, the designations DFA1, DFA2, DFA3 are considered to be associated with polynomials of order 1, 2, 3, etc. Here, we use linear fitting of the trend.

(3) Estimation of the root mean-square fluctuation $F(n)$ around the local trend

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

(4) Analysis of fluctuations over a wide range of n

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

The scaling exponent α is estimated by plotting the dependence (3) in the double-logarithmic plot. When dealing with relatively short data sets, the segmentation is applied twice, in the forward and reverse order, respectively.

On the basis of α, the correlation analysis of the time series $x(i)$ is performed taking into account the relationship between α and the scaling exponent γ of the correlation function $\Psi(\tau) \sim \tau^{-\gamma}$ [27]. The values $\alpha < 0.5$ characterize anti-correlations in the data, when the large and small values of $x(i)$ show the tendency to alternation. In contrast, the power-law correlations with a higher probability of the following large values after large values and small values after small values are quantified by $\alpha > 0.5$. With a further increase in the scaling exponent ($\alpha > 1$), the positively correlated behavior remains, however, it may become distinct from the power-law statistics. The value α=0.5 corresponds to uncorrelated dynamics, and α=1 refers to $1/f$-noise.

Statistical analysis of inter-group differences with the exponent α was performed based on the Mann–Whitney test. We used the value p <0.01 to validate significant distinctions.

3. Results and discussion

The decision-making process for implementing motor functions is very fast. In this study, we consider EEG fragments lasting 3 s, which include not only the decision itself, but also the electrical activity of the brain after this event. Thus, each analyzed data set is characterized by a time-varying structure. DFA allows us to process even smaller amounts of data; however, when the asymptotic scaling exponent is computed, possible crossover phenomena should be taken into account. In physiological studies, e.g., the crossover point can be associated with a change in the correlation characteristics for short- and long-range correlations [28]. In this regard, we compared the dependencies of $F(n)$ for three states: RAM, IAM and background (BCG) electrical activity of the brain. Typical dependencies for RAM and IAM are shown in Fig. 1a and confirm that the main differences are related to the region of relatively long-range correlations. For $\lg n < 1.4$, the slope decreases, and there are no significant distinctions (p >0.05). That is why we considered the range of $\lg n \in [1.4, 2.2]$ for computing the scaling exponent α. The same range of scales enables differentiation between IAM and background EEG, although the observed changes in the scaling exponent are typically smaller. This range is usually related to the main differences in long-range correlations for IAM in comparison with RAM and BCG for other subjects.

The obtained results allow us to suppose that all the considered states can be clearly separated with the DFA-based correlation analysis. Aiming to confirm this supposition, we conducted a statistical analysis of a series of repeating events. Fig. 1b shows the obtained results for the Cz-channel in one volunteer. According to this Figure, there is a distinction between RAM and IAM, as well as between IAM and the background electrical activity of the brain. The Mann–Whitney test verifies that the observed differences are significant (p <0.01). That is why it is possible to separate not only real movements and their imagination, but also imaginary movements and background EEG, which is more important in the creation of BCI. Note, that similar results are obtained when using second-order polynomials to fit the local trend.

The separation depends on both, the selected channel and the volunteer. For some volunteers, the separation between RAM and IAM is possible for all channels (Fig. 2a). For other volunteers, the number of the related channels becomes smaller, and the observed distinctions for some channels are comparable with the variability of α for a series of identical events (Fig. 2b). We compared also several durations of EEG segments, namely 2.5 s, 3 s and 4 s. The results were relatively stable, and the separation between EEG records related to distinct types of movements was qualitatively similar.

Our results confirm that the appropriate selection of EEG channel can provide more pronounced differences. This is confirmed also for a more complicated problem – the separation between IAM and background EEG (Fig. 3). Despite variations of α are less expressed in the case of IAM compared to RAM, a number of EEG channels can be selected where

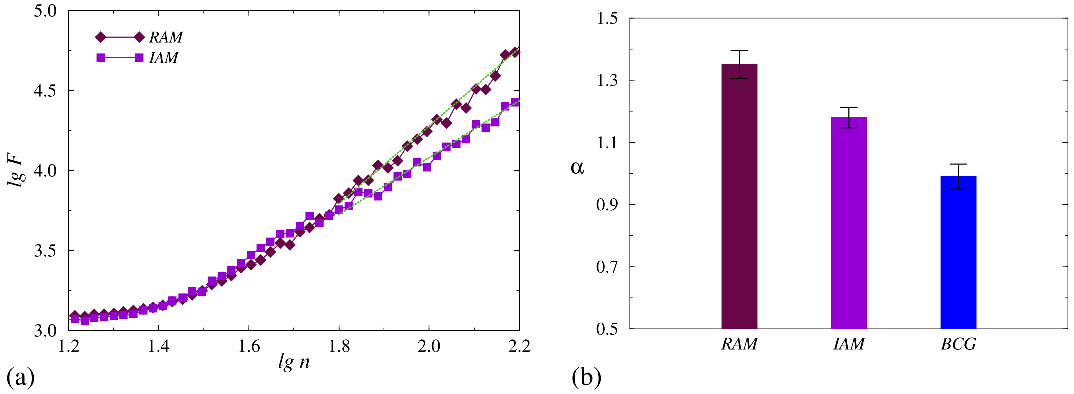

Fig. 1. Typical results for RAM and IAM (a), and scaling exponent computed using the *Cz*-channel of EEG (b). Here and further, the results are given as mean±SE.

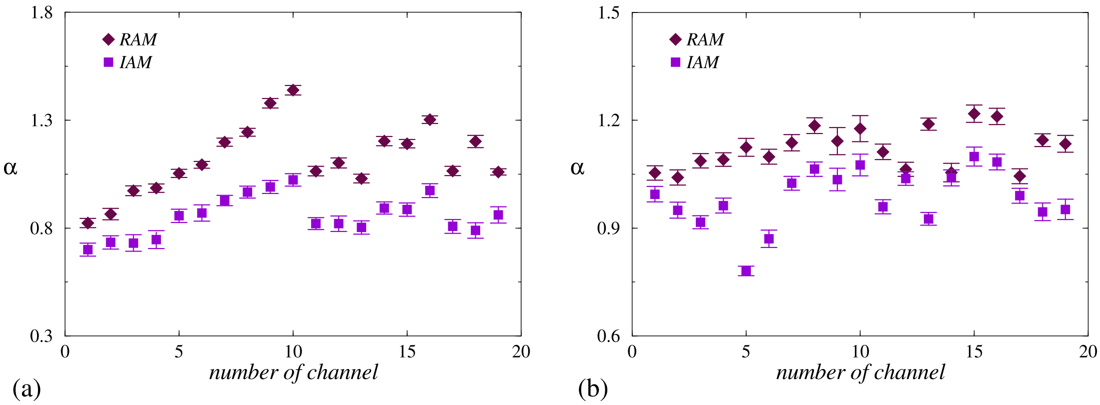

Fig. 2. The separation between RAM and IAM observed in all EEG channels (a) and in almost all channels (b).

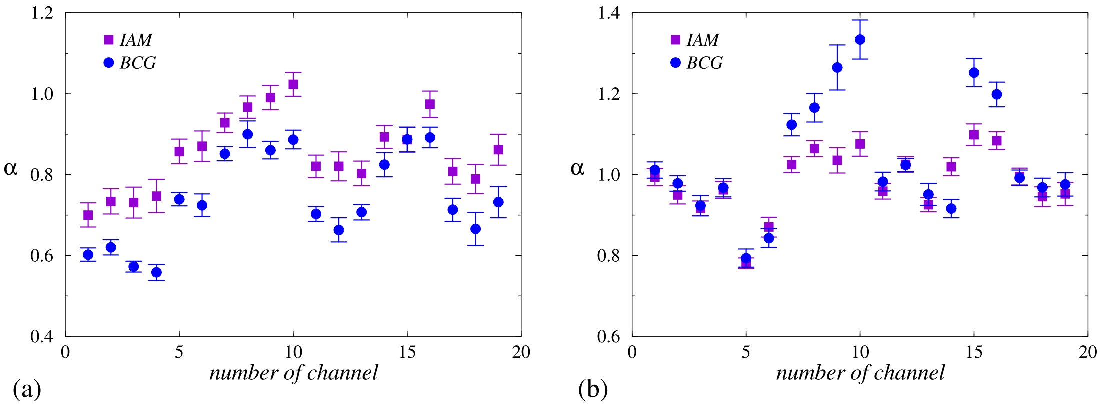

Fig. 3. The separation between IAM and background EEG observed in almost all EEG channels (a) and in a part of the channels (b).

the changes become significant ($p < 0.01$). Table 1 illustrates the number of such channels for each volunteer. Following this table, the recognition of specific EEG patterns is rather the rule than the exception. Distinctions in the number of channels may be caused by different learning abilities and individual concentration peculiarities, because the best results of deciphering mental commands can be revealed in trained volunteers [38,39]. This assumption was partly confirmed in repeated experiments with the same volunteer, where a better separation between IAM and background EEG was reached after repeating the experiment a few days ago (Fig. 4). However, the latter conclusion requires additional, more detailed experiments that can be performed in further researches.

Table 1
The number of channels with the authentic separation between RAM and IAM (N_1) and between IAM and background EEG (N_2).

Volunteer	N_1	N_2
1	17	7
2	19	18
3	14	16
4	19	17
5	18	18
6	14	12
7	17	16
8	19	19
9	19	11
10	18	15

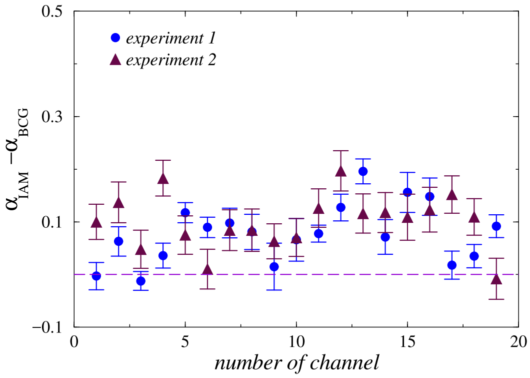

Fig. 4. Improved separation between IAM and background EEG for repeated experiment. Mean difference between scaling exponents increases from 0.081 (experiment 1) to 0.099 (experiment 2).

From the point of view of the practical implementation of BCI, it is important to choose a region of the brain with the most pronounced differences between the considered physiological states, because the analysis of EEG signals from this region can be more effective in distinguishing the types of brain dynamics. Our analysis shows that there is no unique distribution. Fig. 5 illustrates an example of distributions for a subject with strong differences between RAM, IAM and background activity. We can see that the distinctions between IAM and background EEG (Fig. 5a) are more expressed in central areas and become less expressed in the frontal and occipital areas. Processing EEG signals from the latter areas did not reveal strong changes in scaling exponents. According to Fig. 5b and 5c, the clearest distinctions between RAM and background electrical activity, as well as between RAM and IAM appear in the occipital area. For other subjects, the related distributions may differ. That is why the question of finding the most suitable area of the brain to be used for BCI-related studies requires additional investigations and larger statistics to highlight the most common effects of brain electrical activity associated with mental intentions.

4. Conclusion

In this paper, we considered the problem of separating between real and imaginary arm movements, as well as between background EEG and the imagination of motor functions. Due to short and time-varying signals of the brain electrical activity, we used the detrended fluctuation analysis, which is one of the widely applied tools that enable a correlation analysis of nonstationary processes. Our analysis revealed significant distinctions in long-range correlations for RAM and IAM that were observed in all subjects and in the majority of EEG channels. These results show the ability to distinguish between real movements and their imagination, even for short data sets, which is important for the potential application of the used approach as a recognition algorithm in BCI. We also demonstrated the possibility of solving a more complicated and important task of detection mental intentions related to the movements of arms. This possibility was also observed in all subjects, although the number of suitable channels and the absolute changes in scaling exponents related to mental intentions decrease compared to real movements.

Let us note that the obtained results offer new open questions, in particular, on the selection of brain areas with the most essential changes in electrical activity occurred during mental intentions. The preliminary results of this study show that individual features of subjects provide variable distributions of the most pronounced differences between the physiological states considered, and additional experimental researches could elucidate the role of distinct brain areas more clearly. Another open question consists is the role of the training procedure. We suppose that the observed strong variability in

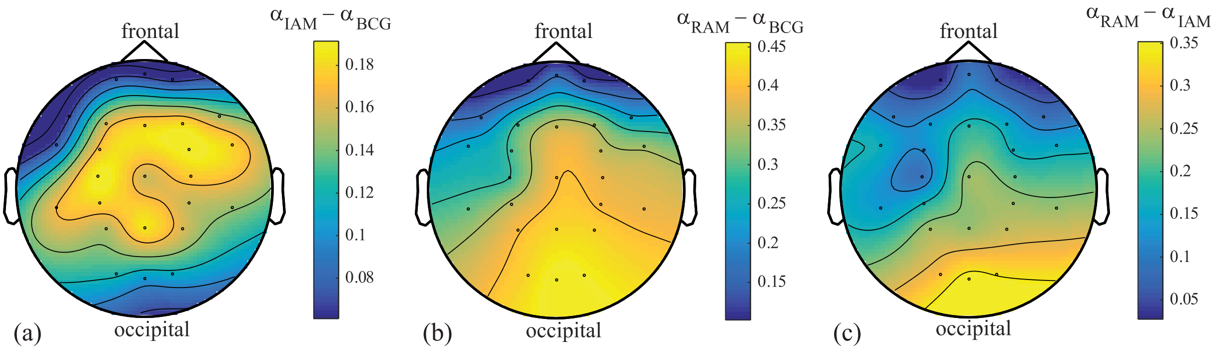

Fig. 5. An example of differences between mean values of α.

the distribution of electrodes with the most significant changes in EEG signals during IAM can be caused by experimental studies with untrained volunteers, and a preliminary training could provide more stable results.

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