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Recognizing human movements by processing EEG-signals using multiresolution analysis

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ABSTRACT

The ability to recognize certain oscillatory patterns in human EEGs associated with various types of movements is studied on the basis of multiresolution analysis, which uses discrete wavelet-transform with Daubechies functions. It is shown that the dispersion of wavelet-coefficients at distinct levels of resolution enables to distinguish the background electrical activity of the brain, the movement of the arms/legs and the imaginations of different types of movements. The advantage of using wavelets with larger support for improving the quality of recognition is discussed.

Keywords: pattern recognition, electroencephalogram, oscillations, wavelet

1. INTRODUCTION

The brain-computer interfaces (BCIs) are devices that enable to perform certain actions in the world around using mental intentions instead of muscles.[1,2] Such devices have been developed over the past few decades, and current progress in both, general knowledge about the brain functioning and technology has provided new opportunities for creating more advanced BCIs.[3–6] Among such devices, non-invasive BCIs are the focus of interest, and the main attention is on improving their properties and achieving characteristics close to invasive ones. Thus, BCIs were designed to control the position of the cursor on the monitor screen[2] and to enable communication for paralyzed people.[1] The main successes in creating BCIs are described in a review paper by Choi et al.[7]

BCIs that are based on the analysis of the electrical activity of the brain (electroencephalograms, EEGs), must identify specific patterns of EEG-signals, recognize them and convert the recognition results into the appropriate control commands for the mechanical part of the interface. The latter requires the availability of software for online processing of electrophysiological data. Software is an important part of BCI, which should provide analysis of short-term, noisy and nonstationary recordings, and the less data can be used for pattern recognition, the better characteristics of the response speed can be achieved. As a rule, a trade-off between processing speed and pattern recognition accuracy is preferred. Because many standard approaches to data processing, e.g., spectral or correlation analysis, require relatively long data sets and do not imply a time-varying structure of experimental data, special time-series methods, e.g., wavelet-based tools,[8–11] detrended fluctuation analysis[12] and other techniques are widely considered for processing neurophysiological signals.

In previous studies,[13,14] we used the wavelet-based multifractal formalism and the DFA-approach for these purposes. The given methods showed the abilitity to recognize mental intentions and real movements of the arms and legs against the background EEGs. However, the use of continuous wavelet-transform[13] is a disadvantage, resulting in significantly increased speed of EEG-processing. Due to this, here we study the abilities of multiresolution analysis which is based on discrete wavelet-transform with fast (pyramidal) signal decomposition schemes. We show that wavelets with larger support are preferable for better recognition of EEG patterns. The paper is organized as follows. In Sec. II we briefly describe the experimental procedures and approaches used for data processing. Sec. III contains the main results obtained and their discussion. Concluding remarks are given in Sec. IV.

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2. MATERIALS AND METHODS

2.1 Experiments

Experimental procedures were carried out on young volunteers (students, n=10) in accordance with the protocol approved by the ethics committee at the Yuri Gagarin State Technical University of Saratov. EEG recordings were performed using the electroencephalograph "BE Plus LTM" (EB Neuro SPA) that was registered with the certificate No. FSZ 2011/10629 (issued by the Russian Federation Federal Service of Health Care and Social Development Control, 20.09.2011). This equipment also complies with the certificates UNI EN ISO 9001/ISO 9001:2008, EN 46001 ISO 13485:2012, QSR 21 CFR Part 820 Federal Law. We used the standard 10-20 setup, which produces 19 channels of data recordings. Data analysis was done on the basis of these pre-registered multichannel signals.

Each experiment included recording the background electrical activity of the brain (10 minutes, divided into two parts, at the beginning and at the end of data collection) and signals related to several tasks, such as raising the left/right arm, lifting the left/right leg, and imagination of these movements. Each task was performed by an audible signal and data fragments for 3 seconds after the related signal were extracted to search for possible distinctions from background measurements. In an effort to identify significant differences between background activity, real and imaginary movements, each type of data was recorded 100 times. In addition, to avoid adaptation to the same type of tasks, a random order of sessions with 20 repetitive movements or imaginations was considered. Volunteers were instructed before the experiments and followed short instruction on the monitor screen during recording.

2.2 Data analysis

As an approach to data processing, we used multiresolution analysis,[8] which performs signal decomposition using a set of scaling functions $\varphi_{m,k}(t)$ and wavelets $\psi_{j,k}(t)$:

$$x(t) = \sum_k s_{m,k}\varphi_{m,k}(t) + \sum_{j\geq m}\sum_k d_{j,k}\psi_{j,k}(t). \tag{1}$$

Such decomposition can be applied for any signal $x(t) \in L^2(R)$ and for an arbitrary selected resolution level m. Scaling functions and wavelets represent low-pass and high-pass filters that are introduced by translation and dilation of the functions $\varphi(t)$ and $\psi(t)$:

$$\varphi_{m,k} = 2^{m/2}\varphi(2^m t - k), \quad \psi_{j,k} = 2^{j/2}\psi(2^j t - k). \tag{2}$$

They must be localized and regular, and $\psi(t)$ must have zero mean value. Transitions between resolution levels j and $j+1$ are treated as a change of time scale (from t to $2t$). The functions used have the following relationships when changing the resolution level:

$$\varphi(t) = \sqrt{2}\sum_{k=0}^{M-1} h_k\varphi(2t-k), \quad \psi(t) = \sqrt{2}\sum_{k=0}^{M-1} h_{M-1-k}\varphi(2t-k). \tag{3}$$

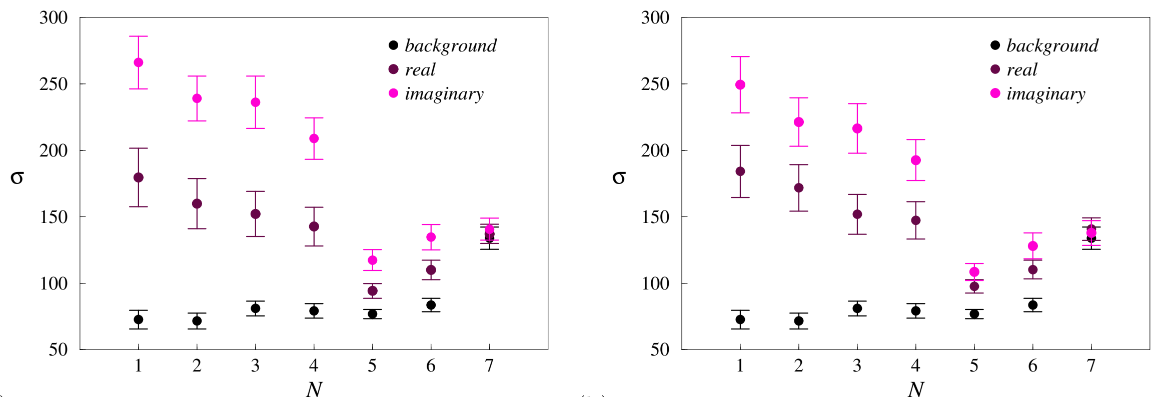
The coefficients h_k, $k = 1, \ldots, M$ are computed numerically using the general features of $\varphi(t)$ and $\psi(t)$: the orthogonality of $\varphi(t)$ and $\varphi(t-k)$, the orthogonality of $\psi(t)$ and $\varphi(t-k)$, the regularity of $\psi(t)$, etc. Depending on the requirements of regularity and the support length, different functions are selected. As a rule, wavelets of the Daubechies family D^n are used in numerical analysis,[9] and the signal under study is decomposed using a pre-selected wavelet basis. The coefficients $d_{j,k}$ reflect the most important features of the signal $x(t)$. In many diagnostic-related studies, the standard deviation of $d_{j,k}$ is used as an informative measure of complex data organization

$$\sigma(j) = \sqrt{\frac{1}{N}\sum_{k=0}^{N-1}[d_{j,i} - < d_{j,i} >]^2}. \tag{4}$$

where N is the number of expansion coefficients, which varies depending on the resolution level j. Based on previous studies of different research groups and the results of our preprocessing of multichannel EEGs, here we considered the resolution level $j = 5$ and the corresponding measure $\sigma = \sigma(5)$. We also selected different functions of the Daubechies family to search for the best separation between various EEG patterns.

3. RESULTS AND DISCUSSION

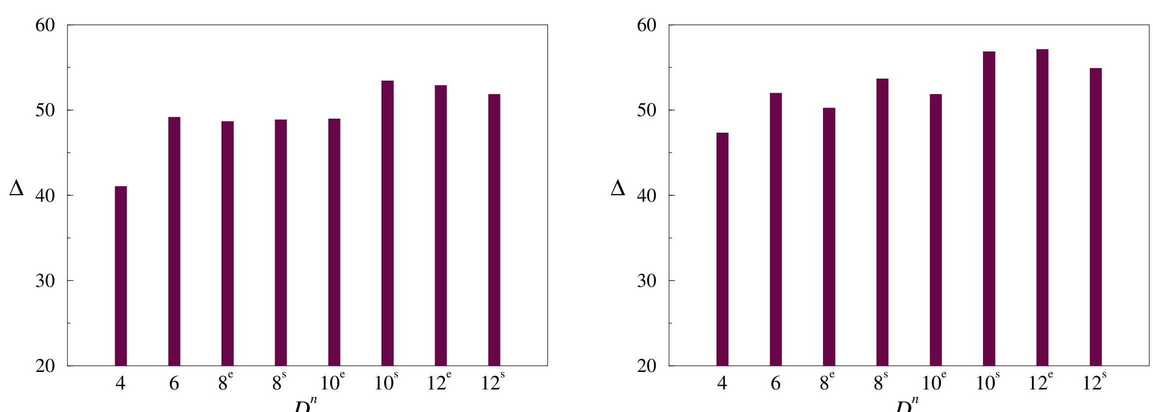
The separation between the background electrical activity of the brain and the related activity during real and imaginary movements was investigated starting with the arms movements. Figure 1a shows an example of the results obtained for the first seven EEG channels. This choice was made to show that there are channels with significant distinctions between the three data sets examined (here, channels 1–6) and channels with poor separation (channel 7). For other channels (not shown in Figure 1a), similar results are observed, consisting in varying distinctions between data sets. Moreover, analogous results are fairly typical for all volunteers, although the distinctions between real and imaginary movements may differ. Thus, the case of stronger changes in the σ values during imagination is found in Figure 1a, while the case of real movements can lead to large distinctions from the background electrical activity of the brain for other volunteers. Nevertheless, the data sets under study are well separated, taking into account the individual peculiarities of each volunteer participating in experimental studies. The number of channels with poor separation between the three states under study also varies.



(a) (b)

Figure 1. The separation between the background EEG, the real and imaginary movements of the right arm (a) and right leg (b) observed for typical experimental data of the electrical activity of the brain, studied using multichannel EEG. Similar results were obtained for the left arm/leg.

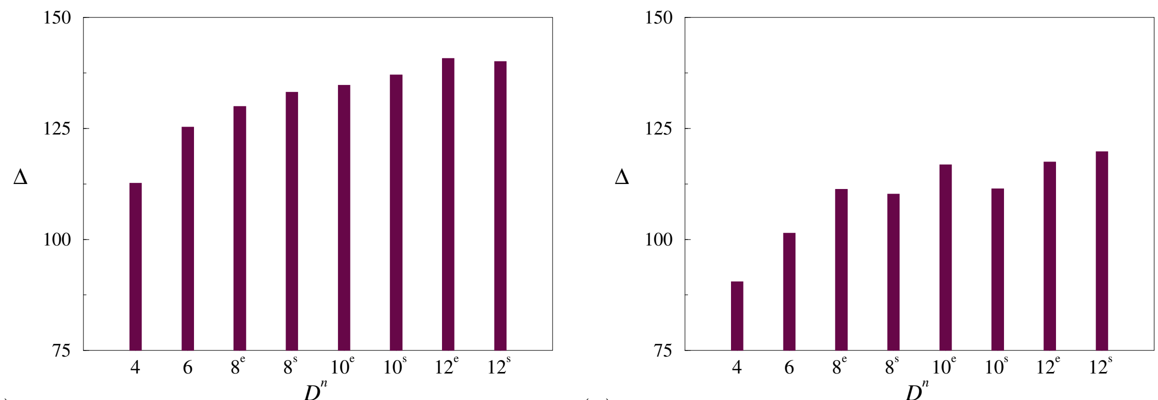
An analysis of leg movements provides similar results (Figure 1b). Visually, the distinctions between Figures 1a and 1b are quite small, but the case of arm movements in the selected example enables us to detect real and imaginary movements using 6 channels of 7, while authentic detection of leg movements is observed for 4 channels of 7.



(a) (b)

Figure 2. The separation between the real movements and the background EEG for the 3rd channel in typical experimental data of the electrical activity of the brain for cases of movements of the right arm (a) and right leg (b). The measure Δ is estimated as the difference of σ-values related to the EEG-patterns considered.

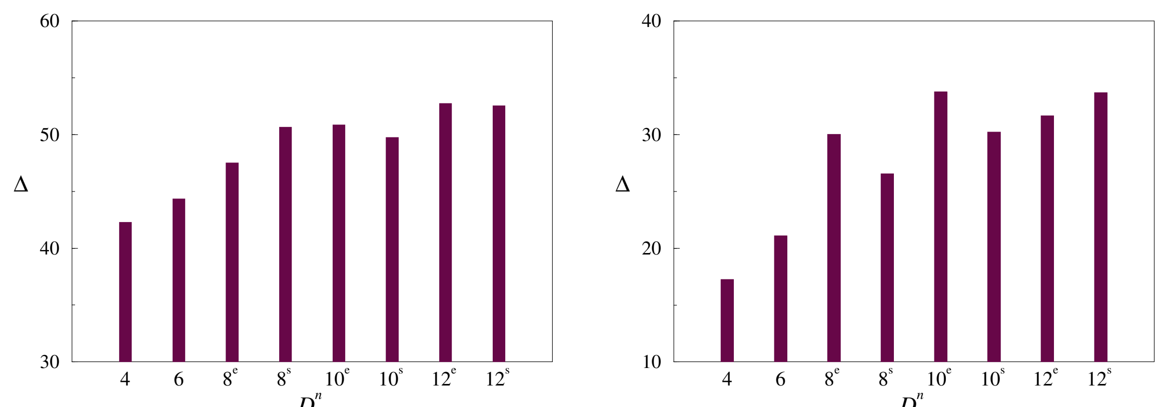
Since the selection of the mother wavelet may affect the quality of pattern identification, we compared the results for distinct bases of the Daubechies family. Figure 2 illustrates the separation between real movements and background EEG in the case of arm movements (Figure 2a) and leg movements (Figure 2b). For Daubechies wavelets D^n with larger support (D^8 – D^{12}), the cases of asymmetric (e) and symmetric (s) wavelets were considered. The results are shown for the 3rd channel as the difference Δ between the averaged values of σ related to real movements and background electrical activity. Despite some variability of the obtained values, there is a tendency of better separability for larger n. This tendency is associated with both types of movements being studied.



(a) (b)

Figure 3. The separation between imaginary movements and the background EEG for the 3rd channel in typical experimental data of the electrical activity of the brain for cases movements by the right arm (a) and right leg (b).

Consideration of imaginary movements also shows the priority of using wavelet-functions with larger support to clearly distinguish between specific patterns related to the imagination of movements and background EEG (Figure 3). Wavelets related to larger n produce increased number of decomposition coefficients and, therefore, the processing speed decreases. However, the pattern detection quality improves, and some compromise between processing speed and possible detection error seems to be preferable.



(a) (b)

Figure 4. The separation between real and imaginary movements for the 3rd channel in the typical experimental data of the electrical activity of the brain for cases of movements by the right arm (a) and right leg (b).

The advantages of using Daubechies wavelets D^n with larger support are also verified by distinguishing between real and imaginary movements (Figure 4). This shows a general trend of better resolution with larger support n, although an appropriate selection of the basic function may improve the recognition results (D^8 and D^{10} wavelets in the case of asymmetric functions are apparently preferable according to Figure 4b).

4. CONCLUSION

Based on the multiresolution analysis that uses discrete wavelet-transform, we studied the ability to recognize specific patterns of electrical activity of the brain related to real and imaginary movements of different types. This ability has been confirmed for a group of 10 healthy volunteers. Despite the number of channels with authentic separation of movement types varies between volunteers, all of them clearly showed the existence of a relatively large number of channels that can be used for pattern recognition. We also showed a general tendency towards a better resolution when using wavelets of the Daubechies family D^n with larger support n. Unlike the previous study,[13] where the multifractal formalism was applied, the approach considered in this paper provides a higher speed of data processing and pattern recognition, which is important for applications such as BCI development.

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