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Recognition of electroencephalographic patterns related to human movements or mental intentions with multiresolution analysis

A.N. Pavlov[a,b,*], D.S. Grishina[a], A.E. Runnova[c,d], V.A. Maksimenko[d], O.N. Pavlova[b], N.V. Shchukovsky[c], A.E. Hramov[d], J. Kurths[e,f]

[a] *Yuri Gagarin State Technical University of Saratov, Politechnicheskaya Str. 77, Saratov 410054, Russia*
[b] *Saratov State University, Astrakhanskaya Str. 83, Saratov 410012, Russia*
[c] *Saratov State Medical University, Bolshaya Kazachia Str. 112, Saratov 410012, Russia*
[d] *Innopolis University, Universitetskaya Str. 1, Innopolis 420500, Russia*
[e] *Potsdam Institute for Climate Impact Research, Telegraphenberg A 31, Potsdam 14473, Germany*
[f] *Institute of Physics, Humboldt University Berlin, Berlin 12489, Germany*

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We study the problem of recognizing specific oscillatory patterns in multichannel electroencephalograms (EEGs) of untrained volunteers arising during various types of movements and mental intentions that are associated with motor functions. To distinguish between the related patterns, we perform a multiresolution analysis based on discrete wavelet transform with the Daubechies basic functions. Using the standard deviation of the wavelet coefficients characterizing their variability in non-overlapping ranges of scales, we verify the ability to separate EEG segments during real and imaginary movements from the background EEG, which appeared in most recording channels. Recognizing the type of movement, such as, e.g., imaginary movement (i.e., the movement that a person performs mentally) by right arm or left leg, is a more complicated task that often can only be solved in few channels. Nevertheless, such recognition was demonstrated for real movements using about 6–8 channels out of 32, and for mental intentions using 1–2 channels. To improve the recognition of various imaginary movements, preliminary training seems mandatory.

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1. Introduction

Recent progress in the creation of brain-computer interfaces (BCI) has offered a novel area of interdisciplinary research, in which the combined efforts of physicists, neurobiologists and engineers have allowed to propose a number of original developments [1–7]. Despite the relatively long history of this topic, with initial approaches suggested almost fifty years ago [8,9], their transformation into noninvasive devices for people with disabilities required both an improved understanding of brain dynamics and subtle capabilities of recognizing mental intentions. BCI performs an online detection of various features of electrical signals, such as electroencephalograms (EEGs), including a transformation of certain patterns into control commands for the mechanical part, to provide special actions in the surrounding world without the use of muscles [10]. Instead of electrical processes, other sources of information can also be used, such as magnetic or optical signals acquired using functional near-infrared spectroscopy [11,12]. Currently, the proposed noninvasive BCIs enable paralyzed people to communicate [13], control the position of the cursor [14], provide partial synthesis of voice messages, regulate body movements [15], or improve alertness [16], etc. They have been applied in medicine and robotic [17–22]. Main achievements in the creation of BCIs are discussed in a recent review paper by Choi et al. [23].

The software that allows detecting certain EEG patterns and recognizing mental intentions plays a key role in each BCI. To ensure such a stable recognition, the software must be based on suitable numerical methods which can perform data processing using only short fragments of multichannel nonstationary EEG records and reveal authentic differences in data fragments associated with various mental actions. Generally, an appropriate tradeoff between the speed of data processing and the accuracy of pattern recognition should be reached [24]. Methods that perform the processing of relatively long records are ineffective for BCI, since they do not meet the requirement of online recognition of EEG patterns. During the last decades, wavelet-based tools have been widely used in many technical applications [25–29] due to

* Corresponding author.
E-mail address: pavlov.lesha@gmail.com (A.N. Pavlov).

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their ability of localized analysis in both time and frequency domains. Our recent study [30] demonstrated how such tools can be used within BCI that recognizes the movements of human hands. However, the considered approach of multifractal formalism based on a continuous wavelet transform [31,32] represents a tool that is more suitable for scientific research, where a good classification performance is preferable than for technical applications which require a prompt recognition of oscillatory patterns. Practical applications are usually based on fast signal decomposition algorithms using discrete wavelet-transform (DWT) and corresponding basis functions [26,27]. In relation to data processing, such methods are applied for noise reduction, encoding and transmission of information, feature extraction, etc. Multiresolution analysis using DWT has been widely considered in diagnostic studies [33].

Recognizing oscillatory patterns related to mental intentions is a difficult problem due to the high variability of EEG segments acquired under nearly identical conditions, such as the re-solving of the same task. This is caused by an adaptation of the brain reaction that changes significantly when a volunteer repeats certain actions many times. Such adaptation is accompanied by reduced durations of responses generated by neural networks and a change in the structure of time series [34]. The separation between such distinct types of patterns should significantly outperform the normal variability related to the selected state. Such a separation is often easily achieved between the background EEG, which is recorded at rest, and the signals acquired during body movements [30,35]. Instead of real movements, one can also consider the imagination of such a procedure, when a volunteer imagines certain motor actions in his/her mind. Differences between background recordings, real and imaginary movements are clearly found not only among trained people, where the separation between types of EEG fragments is usually more pronounced, but also among untrained volunteers, where the variability of the same type of patterns can be much stronger. Nevertheless, a more detailed separation such as between the real movements of the rigth arm and the right leg, or between the imaginary movements of the right and left legs, is more difficult or even impossible when untrained volunteers do not clearly formulate their mental intentions. Aiming to study the abilitity to distinguish such types of EEG patterns, here we perform a comparative analysis of distinct variants of movements, including both real and imaginary motor actions. Using a multiresolution analysis with the Daubechies family of wavelet-functions, we discuss the opportunity of improving pattern recognition by selecting the appropriate basis. We show that the quality of recognition depends on the position of the electrode, although the individual features of volunteers can strongly affect a reliable identification of mental intentions.

2. Experiments and methods

2.1. Experimental procedure

The experiments were carried out on healthy volunteers, including men and women ($n = 9$) aged from 20 to 44 years old, according to the protocol approved by the local ethics committee for scientific research at the Yuri Gagarin State Technical University of Saratov. Each volunteer signed an informed medical consent to take part in the experiments and agreement to publish the results. He/she also received all necessary explanations about the experimental procedure in advance.

Multichannel EEGs were recorded in a specially equipped laboratory with the electroencephalograph “BE Plus LTM” (EB Neuro SPA) that has a registration certificate No. FSZ 2011/10629 (20.09.2011) from the Federal Service of Health Care and Social Development Control of the Russian Federation. The electroencephalograph also complies with the certificates UNI EN ISO 9001/ISO 9001:2008, EN 46001 ISO 13485:2012, QSR 21 CFR Part 820 of the Federal Law. Besides the standard 10–20 international setup, we used additional electrodes according to the 10–10 international setup placed in intermediate positions to get a total 32 recording channels [36]. The sampling rate was equal to 1000 Hz. The experimental data were preprocessed using pre-recorded EEGs. At the data preprocessing stage, the signals were filtered using a band-pass filter with cut-off frequencies of 1 Hz and 100 Hz, and a notch filter of 50 Hz.

In each experiment, the background activity was measured for 10 min, divided into two parts (5 min at the beginning and 5 min at the end). EEGs related to solving several tasks were acquired in separate sessions, each of which included real or imaginary movements. Thus, we analyzed the electrical activity of the brain when a volunteer raises his/her right arm in the shoulder joint (real movement with the right arm, RAR), left arm (RAL), right leg (RLR) or left leg (RLL). In addition to these raises, volunteers were asked to imagine the movements, and the cases of imaginary movements of the right/left arm (IAR/IAL) and the right/left leg (ILR/ILL) were considered. Each session consisted of 20 real/imaginary movements of the same type. During the experiment, 2–3 sessions were carried out for each type of task. Before the session, a short instruction was reproduced on the monitor screen. The real movement or its imagination was started by a sound signal, and the electrical activity of the brain was measured for 3 s. To avoid the adaptation of volunteers, a random order of sessions was chosen.

2.2. Data processing

The processing of the recorded EEG segments related to movements or imagination of motor functions was performed with the multiresolution analysis [25–27] that decomposes a signal using two sets of mirror filters: (i) low-pass filters $\varphi_{j,k}(t)$ constructed by translations and dilations of the scaling function $\varphi(t)$, and (ii) high-pass filters $\psi_{j,k}(t)$ obtained by similar translations and dilations of the basic wavelet $\psi(t)$:

$$\varphi_{j,k} = 2^{j/2}\varphi(2^j t - k), \quad \psi_{j,k} = 2^{j/2}\psi(2^j t - k). \tag{1}$$

A scaling factor 2^j and data sets containing 2^n samples are usually considered. The features of the functions $\varphi(t)$ and $\psi(t)$ include time-frequency localization and regularity. A neccesary requirement for a wavelet is the presence of at least one vanishing moment. Depending on the localization of signal features at distinct time scales, transitions between resolution levels are provided. Thus, the transition between the levels j and $j+1$ corresponds to a change of the time scale from t to $2t$. If the resolution level varies, the following relationships hold:

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

The number of filter coefficients h_k is equal to $2M$ and varied depending on the wavelet function. They are evaluated by the general properties of the scaling functions and wavelets. The latter properties include the orthogonality of the translated scaling functions $\varphi(t)$ and $\varphi(t-k)$, the orthogonality of wavelets $\psi(t)$ to the scaling functions $\varphi(t-k)$, the regularity and oscillatory behavior of $\psi(t)$, etc [37]. We use here the Daubechies wavelets D^{2M} that possess a maximal number of vanishing moments for a given support length [26]. In the case of the D^4 wavelet, the filter coefficients have an analytic expression:

$$h_0 = \frac{1}{4\sqrt{2}}(1+\sqrt{3}), \quad h_1 = \frac{1}{4\sqrt{2}}(3+\sqrt{3}),$$
$$h_2 = \frac{1}{4\sqrt{2}}(3-\sqrt{3}), \quad h_3 = \frac{1}{4\sqrt{2}}(1-\sqrt{3}). \tag{3}$$

For Daubechies wavelets D^{2M} of higher rank ($M > 2$), the values of h_k are found with a required accuracy by solving the Mth power equation. Such wavelets are smoother compared to D^4 and more regular (they have M vanishing moments). A higher rank ($2M$) enables us to retrieve information on the signal features of higher orders, because polynomial behavior in the data treated as a low-frequency trend will be ignored.

Any signal $x(t) \in L^2(R)$ can be decomposed at an arbitral chosen resolution level m as follows

$$x(t) = \sum_k s_{m,k}\varphi_{m,k}(t) + \sum_{j\ \geq m}\sum_k d_{j,k}\psi_{j,k}(t). \tag{4}$$

To process experimental data, this decomposition is performed using fast (pyramidal) algorithms for sampled values $x(i\Delta t), i = 1, \ldots, K$. The decomposition coefficients $s_{m,k}$ and $d_{j,k}$ provide information about the features of the signal at independent scales.

The set of coefficients $d_{j,k}$ varies over a nonstationary time series. An informative measure of such a variability is the standard deviation, computed as a function of the scale:

$$\sigma(j) = \sqrt{\frac{1}{L}\sum_{k=0}^{L-1}[d_{j,k} - < d_{j,k} >]^2}, \tag{5}$$

where L is the number of wavelet coefficients at the scale j within a selected time interval. The standard deviation $\sigma(j)$ quantifies fluctuations at distinct time scales j, i.e., related to different frequency bands. Its assessment is used to diagnose changes in physiological time series. In particalar, the study by Thurner et al. [33] suggested to use $\sigma(j)$ as a clinically significant measure of pathological changes in heart rate variability. Taking into account recent studies by others and our preliminary results of EEG processing, we select the resolution level $j = 5$ and the related measure $\sigma = \sigma(5)$. In the course of data analysis, we compare different bases of Daubechies wavelets to provide an improved separation between distinct types of EEG patterns.

2.3. Statistical analysis

We used the Student's t-test to determine if two sets of EEG patterns, related to distinct states or types of movements differ significantly from each other. In addition to the t-values, we estimate the number of channels (N) associated with significant distinctions ($t > t_c$), with t_c related to the level of significance p=0.01. The results are shown as the mean values ± SD.

3. Results and discussion

Before studying the differences in EEG patterns related to movements of arms and legs, a simpler task was considered to distinguish real/imaginary movements from background electrical brain activity (BGR). To do this, we selected one type of movement (left arm) and compared the σ values for each the EEG channel. Fig. 1a shows an example of the results for different positions of the electrodes. It illustrates that the separation can be highly dependent on the channel of data registration (see Fig. 1b). Thus, in the occipital (O) and parietal (P) areas, larger values of σ are found associated with RAL and IAL, compared to the background EEG, and there is also a good separation between real and imaginary movements. In the pre-frontal area (F_p), the opposite effect of larger σ-values related to background activity is observed, and the EEG patterns considered can be only poorly distinguished or not divided in the central (C) and frontal (F) areas. In this example, such distinctions occur regardless of the electrode placement on the right side of the head (even numbers of channels) or on the left side (odd numbers).

Fig. 2 illustrates how the differences in the σ values related to real/imaginary movements and the background EEG, namely, $\sigma_{RAL} - \sigma_{BGR}$ and $\sigma_{IAL} - \sigma_{BGR}$, vary along a virtual line on the surface of the head, going from the back of the head to the forehead. These differences are shown separately for electrodes placed on the left (Fig. 2a) and on the right side of the head (Fig. 2b). In both cases, there is a transition from positive to negative values of $\Delta\sigma$, i.e., the position of the recording electrode has an essential influence on the accuracy of pattern recognition. The distributions of $\Delta\sigma$ values over the entire surface of the head are shown in Fig. 3. Let us note that such distributions vary among the volunteers, and differ depending on the type of movement. Therefore, it is generally unclear how to select areas of the head with the most prominent distinctions among the EEG patterns, which are related to different types of movements, and the individual features of volunteers should be taken into account. Due to this, we shall further consider how the number of channels with reliable pattern detection depends on the subject and whether it is possible to improve the diagnostic results by selecting the appropriate wavelet basis?

To answer the second question, we compared the t-values quantifying the distinctions between the measure (5) estimated for movements of the left arm and the background EEG for the family of Daubechies wavelets, including both, the extremal phase wavelets (such wavelets marked by the upper index "e", "bunch up" at the start of their support) and the least-asymmetric wavelets which is more spread out over its support (marked by the symbol "s"). Fig. 4 shows the results for real (Fig. 4a) and imaginary (Fig. 4b) movements, certifying that the selection of a suitable basis can improve the recognition of EEG patterns. In general, the number of channels with a reliable separation increases by about 5% when a more appropriate basis is chosen. Comparing all experimental data recorded in this study, we select the extremal phase wavelet D^8 that provides the best recognition of oscillatory patterns in EEG recordings. This wavelet allows us to get the highest value of t in Fig. 4 and can be considered as a trade-off between wavelet support and the number of vanishing moments.

Next, we analyze how the quality of separation depends on the type of movement and compared the EEG segments associated with raising arms and legs. According to Fig. 5a, the distinctions between real arm/leg movements and the background electrical activity of the brain are fairly small. In both cases, a good separation is achieved for 42–45 channels out of 64. Imaginary movements are divided using a reduced number of channels (33–34 out of 64), but again there is no clear difference between the arm and leg raises. Fig. 5b gives the statistical results of distinguishing real and imaginary movements of the same type. This figure shows the differences between the σ-values related to real and imaginary movements averaged over all persons. In general, the results are rather similar, except for the case of raising the right arm, when a higher number of relevant channels is obtained. However, such distinctions are caused by one volunteer, who demonstrated significant differences between EEG segments associated with right-arm raises in almost all channels. The latter is quite atypical for other experimental data. We suppose that the distinctions will be reduced for more statistics of experiments, when the effect of individual features of some volunteers will be excluded. It can be concluded that, regardless of the type of movement, there are enough channels which enable distinguishing real and imaginary movements.

A more difficult problem is identifying the distinctions between the movements performed by the right leg/arm and the left

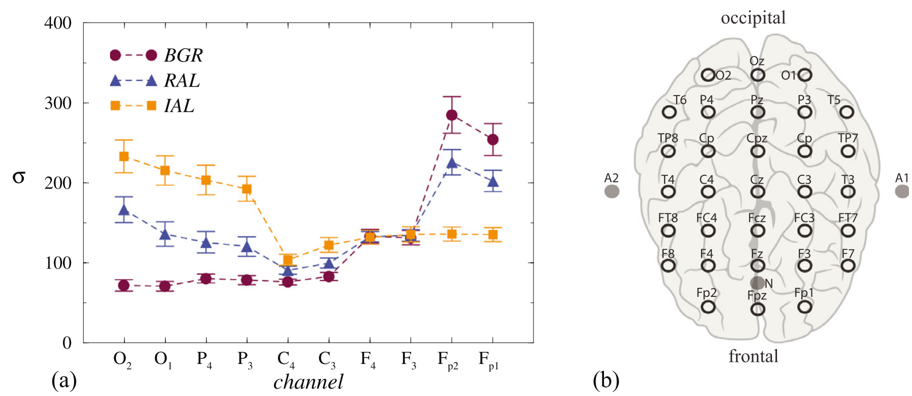

Fig. 1. (a) $\sigma(5)$ values for background electrical brain activity (BGR), real (RAL) and imaginary (IAL) movements with the left arm in a typical experiment (one person, averaging is performed over different trials) depending on the position of the electrode in accordance with the 10–10 setup. The channels selected illustrate how $\sigma(5)$ varies between occipital and frontal areas. They also show non-significant distinctions between electrodes placed on the right and on the left side of the head. (b) Position of electrodes according to the "10–10" international system of EEG recording on the human head. A_1 and A_2 are the reference electrodes positions, N is the ground electrode position.

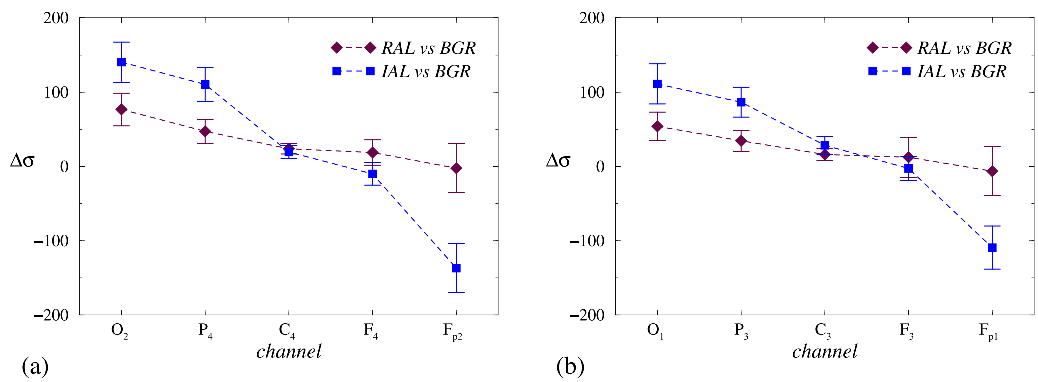

Fig. 2. The differences $\sigma_{RAL} - \sigma_{BGR}$ and $\sigma_{IAL} - \sigma_{BGR}$ estimated along the electrodes placed from the nape to the forehead on the left (a) and on the right side of the head (b).

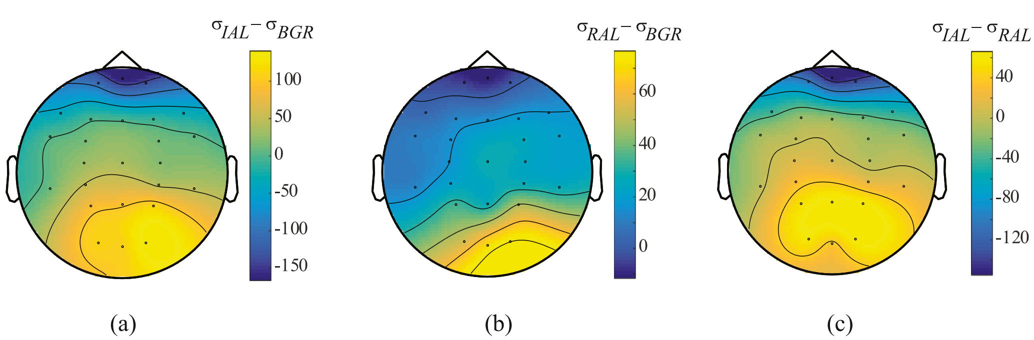

Fig. 3. The distributions of $\Delta\sigma$ values for typical experimental data. Significant distinctions are observed between EEG patterns recorded from occipital and frontal areas.

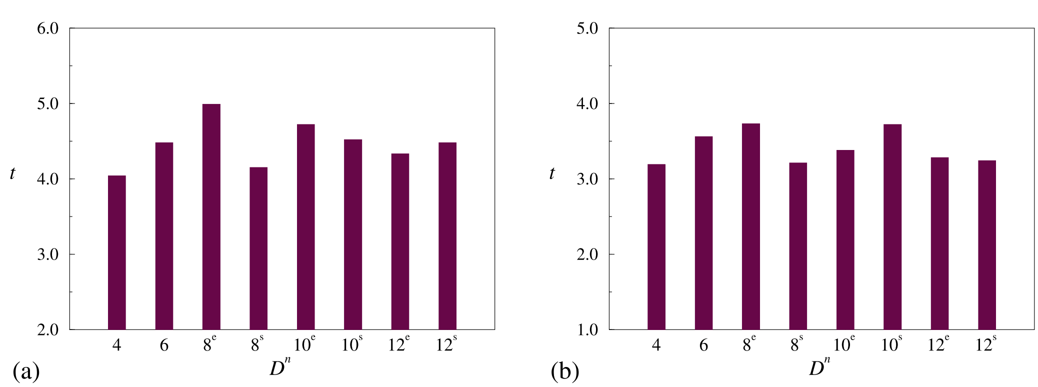

Fig. 4. Comparative analysis of t-values depending on the wavelet basis of the Daubechies family, which characterize the distinctions between EEG patterns in real (a) and imaginary (b) movements with the left arm and background EEG. The upper indexes "e" and "s" denote the extremal phase wavelets and the least-asymmetric wavelets, respectively.

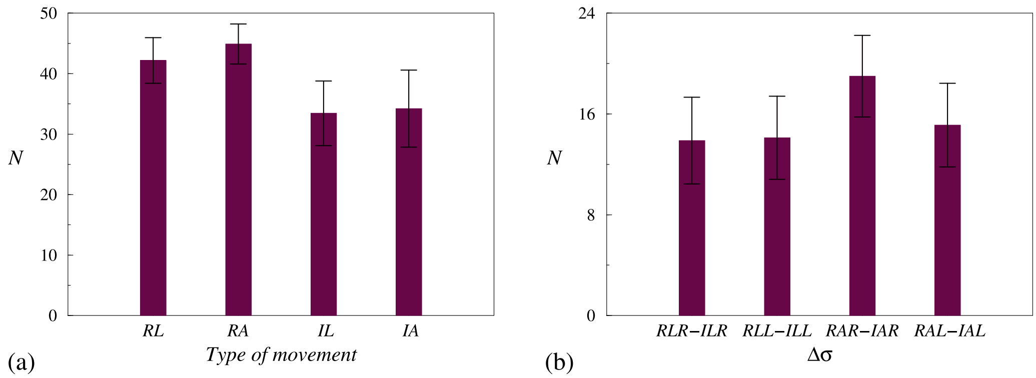

Fig. 5. The number of channels with a reliable separation (a) between real movements with legs (RL) / arms (RA), imaginary movements with legs (IL) / arms (IA) and the background EEG, (b) between real and imaginary movements of different types. Data are given as mean values ± SE.

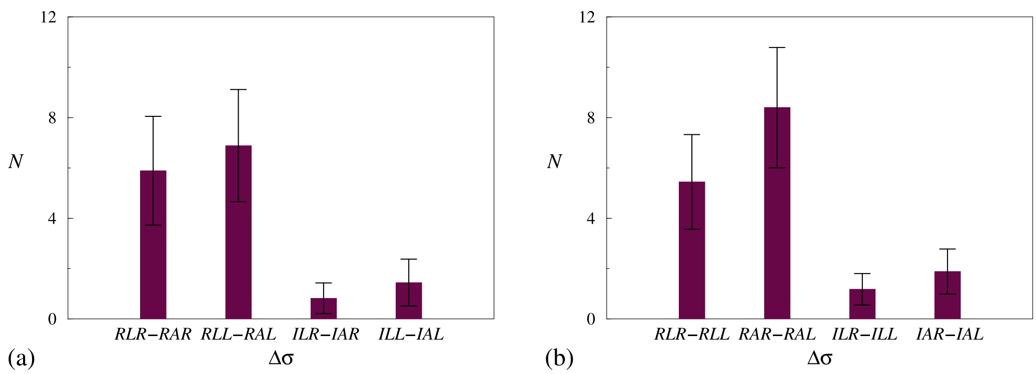

Fig. 6. The number of channels with a reliable separation (a) between the different types of movements with the legs and arms, (b) between the movements of the right and left leg/arm.

leg/arm. For real raises, recognition of related movements is possible for 6–7 channels out of 32 (the case of separation between the left leg/arm and the right leg/arm, Fig. 6a). When dealing with imaginary movements, the number of suitable channels decreases to 1–2. This means that a recognition is possible, although careful selection of a recording electrode can be crucial for understanding the mental intentions associated with motor functions. Another conclusion is that non-trained subjects may formulate their intentions not clearly enough, and a prior training is a mandatory step before using a BCI. Similar statistics are observed for the separation between the raises of the left and right arms, or between the left and right legs (Fig. 6b). The results are comparable to Fig. 6a, namely: 6–8 channels for real raises and 1–2 channels for mental intentions.

4. Conclusion

In this study, we have considered the problem of recognizing EEG patterns associated with raising arms/legs and the mental intentions of distinct motor functions. In experiments with untrained volunteers, cases of 8 movement types were considered and compared with each other, as well as with background recordings of brain electrical activity. Using a multiresolution analysis based on DWT with the Daubechies basic functions, we have analyzed the possibility of distinguishing between certain EEG segments related to the movements or their imaginations. The choice of data processing tool is explained by a rapid procedure of signal decomposition and the possibility of a localized analysis of the experimental data. We have confirmed that the choice of a suitable basis can improve the recognition results, although this improvement is not decisive for general conclusions, i.e., if a recognition is possible, then the number of suitable channels can be increased by 1–2 due to the choice of the wavelet.

The ability to recognize specific patterns of multichannel EEG for different types of movements has been confirmed for a group of 9 healthy volunteers. A recognition is easily performed when the signals related to real/imaginary movements are matched with background measurements. Thus, reliable recognition results have been found in about 70% of the channels (real movements) and in more than 50% of the channels (mental intentions). A comparison of the types of movements (left and right arm/leg) is more complicated procedure, because the distinctions between these types of EEG patterns are less pronounced. Nevertheless, there are EEG channels which allow us to distinguish not only various types of real raises (6–8 channels out of 32), but also mental intentions (1–2 channels). Taking into account that the separation of EEG fragments associated with mental intentions is manifested in a small number of channels, the quality of the formulation of mental intentions by volunteers is crucial for BCI-related applications. If the simplest mental commands are easily formulated by all volunteers, more specific intentions (e.g., moving the right leg or right arm) are usually unclearly formulated without prior training. In our study, only 2 out of 9 volunteers provided clear recognition results without training, and the remaining 7 volunteers needed preliminary experience in formulating mental commands for motor functions. According to our previous research [35], such training usually improves the recognition results.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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