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ABSTRACT

We have considered time-frequency and spatio-temporal structure of electrical brain activity, associated with real and imaginary movements based on the multichannel EEG recordings. We have found that along with well-known effects of event-related desynchronization (ERD) in $\alpha/\mu-$ rhythms and $\beta-$ rhythm, these types of activity are accompanied by the either ERS (for real movement) or ERD (for imaginary movement) in low-frequency $\delta-$ band, located mostly in frontal lobe. This may be caused by the associated processes of decision making, which take place when subject is deciding either perform the movement or imagine it. Obtained features have been found in untrained subject which it its turn gives the possibility to use our results in the development of brain-computer interfaces for controlling anthropomorphic robotic arm.

Keywords: Electroencephalogram, continuous wavelet analysis, brain-computer interface, untrained subject

1. INTRODUCTION

Developing the brain-computer interfaces (BCI) is a very important and challenging task in medicine for epilepsy control and prevention,[1–3] in robotics for exoskeleton control,[4] in work with people with disabilities.[5] It is known that the features of brain activity, associated with real and imaginary movements can be effectively used for generation of control commands for BCI systems,[6] including control of anthropomorphic robots.[7,8]

There are plenty of techniques for analyzing neurophysiological features of different brain states and different types of behaviour with the aim of their transformation into commands for controlling computer, medical or robotics systems. For this purpose, one can use event-related potentials,[9] algorithms of machine learning and artificial intelligence,[?,10,11] techniques for isolating the time-frequency structure of the signals,[12–14] and methods for restoring connections between different brain areas using multichannel data.[15–18]

At the same time, in the case of imaginary movements these techniques demonstrate positive results for trained subjects.[19] For untrained subjects extraction of motor-related features of brain activity is the more challenging task, however less studied.[20] Existing motor imagery classification algorithms being applied to untrained participants do not always achieve good performances because of the noisy and non-stationary nature of the EEG signals and inter-subject variability.[21]

In the framework of current research topic in this paper we analyze spatio-temporal and time-frequency characteristics of electrical brain activity associated with different types of motor actions in the group of untrained subjects based on wavelet analysis of multichannel EEG.

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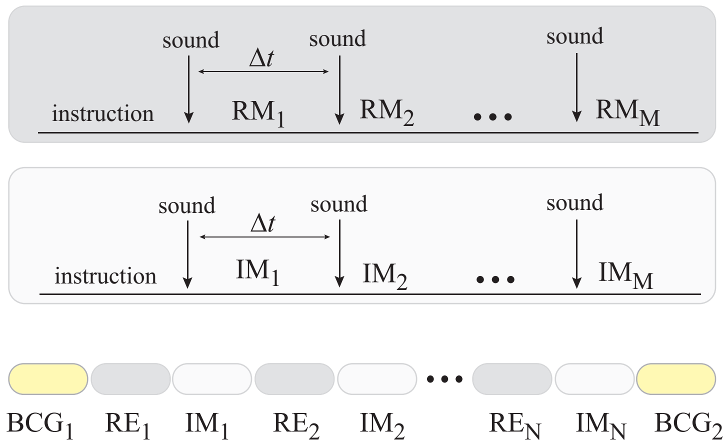

Figure 1. The structure of experimental sessions: RM_i and IM_i ($i = \overline{1, M}$ — the number of individual event in the session) define a single real and imaginary movement, respectively. $M = 20$ is the total number of events in the session, $\Delta t = 4$ s is the time interval reserved for the task. Each session is preceded by a video message with instructions and each event in the session is preceded by an audio message. RE_j and IM_j ($j = \overline{1, N}$ — the session number) correspond to the sessions in which the real and imaginary movements take place, respectively, $N = 5$ is the total number of sessions, associated with each type of movement. The experiment starts with a 5-min background EEG recording (BCG_1) and ends with a 5-min background recording (BCG_2).

2. METHODS

Healthy volunteers including both males and females, between the ages of 20 and 43 participated in the experiments. All of them signed a written consent. The experimental studies were performed in accordance with the Declaration of Helsinki and approved by the local research Ethics Committee of the Yuri Gagarin State Technical University of Saratov.

The multi-channel EEG was recorded at 250 Hz sampling rate from $P = 52$ electrodes with two reference electrodes placed at the standard positions of the 10–10 international system.[22] To register EEG data we used cup adhesive Ag/AgCl electrodes. The ground electrode N was located above the forehead and two reference electrodes $A_{1,2}$ were located on mastoids. The EEG signals were filtered by a band pass filter with cut-off points at 1 Hz (HP) and 100 Hz (LP) and a 50-Hz Notch filter. The electroencephalograph"Encephalan–EEGR–19/26" (Taganrog, Russian Federation) with multiple EEG channels was used for amplification and analog-to-digital conversion of the EEG signals.

Each of twelve participants was subjected to one experiment, lasting approximately 30 minutes. During the experiment a volunteer was instructed to perform two types of tasks: to lift slowly the right hand (in the shoulder joint) and imagine such a movement during a given time interval. The whole experiment was split into 10 sessions, 5 sessions of real movements and 5 imaginary movements . Each real-movement session followed by imaginary-movement session. The experiment started with a 5-min background EEG recording and ended with a 5-min background recording. Each session was preceded by a short visual message with instructions and contained $M = 20$ identical events. Each event in the session was preceded by a short sound message and should be performed within a reserved time interval $\Delta t = 4$ s. The experiments were carried out during the first half of the day at a specially equipped laboratory where the volunteer was siting comfortably and effects of external stimuli, e.g. external noise and bright light, were minimized.

Time-frequency analysis of EEG recordings was based on the continuous wavelet transform[23,24]

$$W(a, \tau) = \frac{1}{a} \int_{-\infty}^{\infty} x(t) \psi \left(\frac{t - \tau}{a} \right) dt \tag{1}$$

where complex-valued Morlet-wavelet was chosen as the mother function[25]

$$\psi(\eta) = \pi^{-1/4} \exp(i\omega_0\eta) \exp\left(-\frac{\eta^2}{2}\right), \tag{2}$$

with $\omega_0 = 2\pi$ being the central frequency of the used Morlet mother wavelet and $i = \sqrt{-1}$.

The wavelet energy spectrum

$$E_i^n(t,f) = (W_i^n)^2(t,f), \tag{3}$$

was calculated in the frequency band $f \in [1,30]$ Hz ($f = 1/a$) for each EEG channel n and each EEG trial i (length of 4 seconds), associated with either real or imaginary movement. For each type of movement and for background EEG, the values of wavelet energy $E^n_{\mathrm{RE}}(t,f)$, $E^n_{\mathrm{IM}}(t)$, $E^n_{\mathrm{BCG}}(t)$ were calculated by averaging $E_i^n(t,f)$ over N EEG trials, associated with real movements (RE), imaginary movements (IM) and background EEG (BCG)

$$E^n_{\substack{\mathrm{RE}\\ \mathrm{IM}\\ \mathrm{BCG}}}(t,f) = \frac{1}{N} \sum_{\substack{i\in \mathrm{RE}\\ i\in \mathrm{IM}\\ i\in \mathrm{BCG}}} E_i^n(t,f). \tag{4}$$

For every type of movement and for background EEG the values of whole spectral energy $W^n_{\mathrm{RE,IM,BCG}}(t)$ were calculated for each EEG channel by integrating values $E^n_{\mathrm{RE,IM,BCG}}(t,f)$ over considered range of frequencies[26]

$$W^n_{\substack{\mathrm{RE}\\ \mathrm{IM}\\ \mathrm{BCG}}}(t) = \int_{1\ \mathrm{Hz}}^{30\ \mathrm{Hz}} E^n_{\substack{\mathrm{RE}\\ \mathrm{IM}\\ \mathrm{BCG}}}(t,f')df' \tag{5}$$

Finally, in order to estimate the change in wavelet energy, associated with motor execution or motor imaginary, the differences $E^n_{\mathrm{RE}} - E^n_{\mathrm{BCG}}$ and $E^n_{\mathrm{IM}} - E^n_{\mathrm{BCG}}$ were calculated.

3. RESULTS

At the first stage the values $W^n_{\mathrm{RE,IM}}(t)$, reflected the whole spectral energy of EEG signals, were considered during time interval $t = 4$ s. and compared with such values, calculated for background EEG $W^n_{\mathrm{BCG}}(t)$. These values are shown in Fig. 2. Values $W^n_{\mathrm{RE,IM}}(t)$ are shown by red and green colors and $W^n_{\mathrm{BCG}}(t)$ are shown by dashed lines. One can see that real movement is associated with the increase of wavelet energy in frontal lobe and decrease of the energy in central lobe. Imaginary movement, on the contrary, induces decrease of wavelet energy in frontal lobe, but at the same time causes the increase of the energy in parietal lobe.

In order to clearly understand the time frequency structure of EEG signals the dynamics of dependencies of wavelet energy on time and frequency have been considered.[27,28] In Fig. 3 one can see time-frequency plots which reflect change in wavelet energy, associated with real movement (a) and imaginary movement (b).

One can see that a significant increase for real movement and a significant decrease for imaginary movements of wavelet energy in frontal lobes are mainly determined by the low-frequency (1-5 Hz) δ-waves. The energy of δ-waves exhibited a significant change in frontal area, which decreased rapidly while moving from frontal to parietal lobe. This resulted in a significant change in whole wavelet energy. At the same time, the time-frequency structure of EEG signal is much more complicated. The features of real and imaginary movements were characterized by the transition and distribution of the energy between different frequency bands. Considering real movement (Fig. 3, (a)) one can see that electrical activity in central lobe together with an increase in δ-waves' amplitude is characterized by a decrease of the wavelet energy for $f \in [8,12]$ Hz (μ-rhythm) and decreasing energy in $f \in [15,30]$ Hz (β-activity). This effect is known in scientific literature as *event-related desynchronization* (ERD).[29] The ERD associated with motor activity was previously observed in the frequency

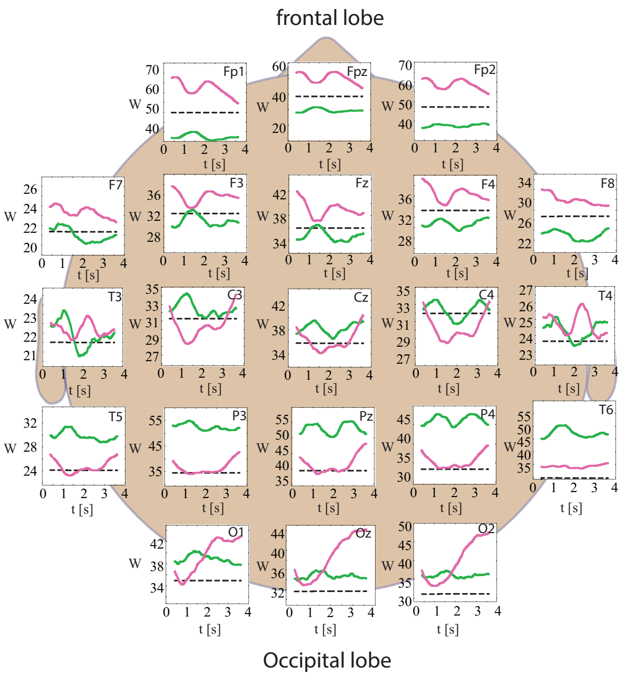

Figure 2. the values $W^n_{\mathrm{RE,IM,BCG}}(t)$, reflected the whole spectral energy of EEG signals, calculated via Eq. (5) Values $W^n_{\mathrm{RE,IM}}(t)$ are shown by red and green colors and $W^n_{\mathrm{BCG}}(t)$ are shown by dashed lines.

bands of 8-10, 10-12, 12-20, and 20-30 Hz.[30] It is known that motor execution is characterized by both event-related desynchronization and event-related synchronization (ERS). The ERD was usually observed in α (or μ) and β-bands,[31] while such effect in δ-band was much less studied.[32] At the same time, according to Fig. 3, (a), event-related synchronization of δ-activity took place during motor execution together with event-related desynchronization of μ/α)- and β-rhythms.

In Fig. 3 (a) One can see that the observed ERD in μ-rhythm prevailed in temporal, central, and parietal lobes, where the motor area took place.[33] It should be noted that this area is shifted from the center to the left side, which is connected with hemispheric asymmetry, associated with arm movements.[34] An accompanying event-related increase in the amplitude of the low-frequency δ-activity was more pronounced in frontal lobe.

Motor imaginary, in turn, was also associated with significant changes in δ-activity, which can be observed in frontal area (Fig. 3 (b)). However, in this case the energy of δ-waves decreased, that was associated with event-related desynchronization. While ERD took place in δ-band, μ-rhythm exhibited event-related synchronization, which was well pronounced in the most areas of the brain, but reached maximal value in central and parietal lobes and significantly decreased in temporal lobes (Fig. 3 (b)).

4. CONCLUSION

The event-related synchronization and event-related desynchronization are known to be associated with motor execution and motor imaginary. These effects were actively studied in the frequency bands of 8–10 Hz, 10–12 Hz, 12–20 Hz and 20–30 Hz. At the same time, event-related desynchronization (ERD) and event-related synchronization (ERS) in low frequency δ-band remains poorly investigated in the case of motor-related brain activity, but known to be associated with decision making.[32] We suppose that such EEG signatures of MI are caused by the lack of subject training. Taking into account[31] one can expect that in trained subjects the time-frequency and spatio-temporal structure of EEG signals, corresponded to imaginary movement, is very similar to once, corresponded to real movement. In this case application of the proposed method is expected to reveal effects of ERD in μ/α- and β-bands instead of ERS, obtained in untrained subjects. In additional, it is expected that, unlike the real movement, ERS will take place in δ-band, which is associated with cognitive

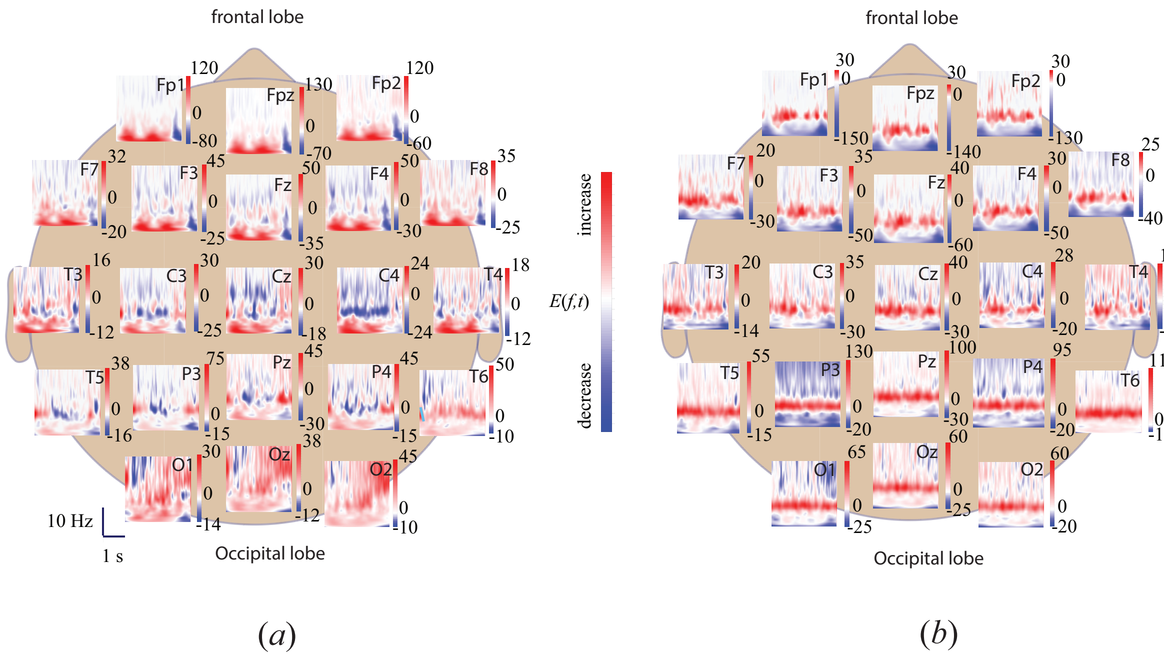

Figure 3. Time-frequency plots of changes in wavelet energy $E(f,t)$, $f \in (1,30)$ Hz, $t \in (0,4)$ s associated with (a) real and (b) imaginary movements with respect to the background EEG. Presented data was averaged over 100 trials and shown for each of 21 EEG channels. Red and blue colors indicate the time-frequency plane for which the energy value, respectively, increased and decreased during real or imaginary movements. Color saturation shows the degree of changes.

activity, associated with decision making,[32] since subject has to decide every time either to move with the hand or not.

We believe that the obtained results are of interest for fundamental science. The revealed motor-related features of EEG signals are valuable for neuroscience and other areas of science and technology aimed to understand brain properties and design brain-computer interface.[5,35] In this context one knows that the efficiency of brain-computer interface is defined by the ability of the operator to generate certain stable EEG patterns. That means that the BMI is affected by operator proficiency and the inter-subject variability.[20] In this respect our results suggest possibility to develop unified ME-MI classifier. This possibility in its turn can be applied for developing brain-computer interfaces for multiple and untrained users.[21] At the same time the obtained features can be used to form commands a brain-computer interface system that was developed to allow direct cortical control of 4-7 active degrees of freedom in a anthropomorphic robotic arm. First preliminary experiments with corresponding equipment of “Android Technics” (Magnitogorsk, Russian Federation; WWW: https://npo-at.com) demonstrate high efficiency of obtained brain-computer interface for control of the translation and rotation of a robotic arm.

5. ACKNOWLEDGMENTS

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