Features of real and imaginary human motor activity with EEG and fNIRS

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***Abstract*—Experimental design for recording of EEG and fNIRS during performance of real and imaginary movement was proposed. Set of experiments was conducted in accordance with this design and obtained EEG and fNIRS dataset was analyzed. Analysis allowed to introduce certain features in time-frequency domain that can be used to separate real motor activity from motor imagery.**

***Index Terms*—electroencephalogram, functional near-infrared spectroscopy, real motor activity, motor imagery, time-frequency analysis**

I. Introduction

Modern studies of brain activity attract researchers from various fields of science due to interdisciplinary nature of problem. Considerable progress in spheres of experimental and data processing methods provides opportunities for vast and detailed studies of specific phenomena in brain neural network. Recent works in this field combine approaches of mathematics, physics and nonlinear dynamics with neurophysiological and biological view on the processes in brain neural structures [1]–[7].

Motor activity and related mental tasks are widely used in development of brain-computer interfaces (BCIs). BCI performs an online detection of various features of brain signals and transformation of certain patterns into control commands for the mechanical part, to provide special actions in the surrounding world without the use of muscles [8]–[10].

The ultimate goal of BCI is possibility to generate control commands without any muscular activity. In this case motor imagery tasks (or imaginary movements without real neuromuscular activity) become good candidates. Motor imagery, sometimes is considered to be a conscious use of unconscious preparation for an actual movement. Previous studies outlining the similarities between real motor activity and motor imagery [11]–[13]. In terms of application in BCI the main question is whether motor imagery follows the same cortical layout as motor execution in the primary motor cortex (M1).

The most wide-spread method for investigation of brain activity is electroencephalogram (EEG) [14]. EEG is commonly used to obtain information about electric activity in different parts of brain in its normal or pathological state. EEG signal being a product of complex neuronal network is characterized by complex time-frequency structure with number of specific frequency ranges, oscillatory patterns, noise components (artifacts), etc. [15] It is well-known, that there is a strong correlation between EEG rhythmic activity and functional state of organizm [16], which can be used in studies on specific states, for example, related to real and imagery motor activity [17]–[19].

Another popular method for estimation of brain activity is functional near-infrared spectroscopy (fNIRS) [20], [21]. Despite lower temporal resolution and time delay of the hemodynamic response compared to EEG signals, fNIRS represents another approach to obtain information about brain activity, which can be complementary to information provided by EEG analysis.

In this paper we performed combined analysis of EEG and fNIRS data acquired during human's motor execution and motor imagery. We performed analysis of EEG signals with help of CWT and analysis of hemodynamics acquired through fNIRS. We found that there are certain features on both EEG and fNIRS signals related to different types of motor activity. We showed that EEG and fNIRS analysis can be combined for greater efficiency.

II. Methods

Twenty conditionally healthy volunteers (20-40 years, men and women both), right-handed, amateur practitioners of physical exercises, and non-smokers participated at the experiment. All of them were asked to maintain a healthy life regime with an 8-hrs night rest during 48 hrs prior the experiment. Each participant provided informed written consent before participating in the experiment. The experimental procedure was performed in accordance with the Helsinki's Declaration.

Design of experiment suggested simultaneous recording of two types of signals: electroencephalogram (EEG) and functional near-infrared spectroscopy (fNIRS).

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EEG is sum of electrical currents generated by a small group of neurons in brain network [14]. For EEG recording we used electroencephalograph"actiCHamp" by Brain Products (Germany). For EEG signal recording we used "ActiCap" — active Ag/AgCl electrodes (one for each EEG channel) placed on the scalp with the help of special cap. To increase the skin conductivity we treated scalp skin with abrasive "NuPrep" gel before the experiment and placed EEG electrodes on conductive "SuperVisc" gel. After the electrodes were placed, we monitored the impedance to get best possible quality of EEG recordings. Common impedance values were < 25 kΩ which is quite sufficient for active EEG electrodes. EEG signals were recorded with sampling rate of 1000 Hz and filtered by band-pass filter (cutoff frequencies at 0.016 Hz and 70 Hz), as well as 50-Hz notch filter.

fNIRS is a noninvasive, relatively low-cost, portable optical brain-imaging technique [20]. It uses near-infrared light to measure changes in oxygenated (HbO) and deoxygenated (HbR) hemoglobin levels due to the hemodynamic response, the rapid delivery of oxygenated blood to active cortical areas through neurovascular coupling [21].

In the common configuration for fNIRS recording, light sources and detectors are placed on the scalp and two wavelengths of light are transmitted through skin, skull and top layer of the cerebral cortex. fNIRS uses light with two wavelengths: $\sim$ 700 and $\sim$ 900 ηm, that can pass through skin, bone, and water, but are highly absorbed by HbO and HbR correspondingly [22]. Because HbO and HbR have different light absorption properties, the relative changes in HbO and HbR, and therefore the change in oxygenation of the tissue, can be calculated from changes in the reflected dual-wavelength light using the modified Beer-Lambert law [23]. Obtained distributions of HbO and HbR are analyzed for different cortex areas to find ones that are activated during particular real or imaginary movement. We used NIRScout device by NIRx company (Germany) with 8 sources and 8 detectors and time resolution of 7.8 Hz.

According to experimental design EEG and fNIRS electrodes were placed on the subject's scalp at the same time. EEG electrodes were arranged according to international "10-10" scheme — in our case we used 31 EEG electrodes with ground electrode N on the fore head and reference electrode A on the right mastoid. Such EEG electrode placement provides good covering of all important areas of brain including primary motor cortex (M1). Due to the limited number of fNIRS electrodes (8 sources and 8 detectors) all of them were placed in the area of M1. Each pair "source-detector", that were close enough to each other, formed fNIRS channel.

Basic experimental design was the following: subject was sitting in a chair with hands on armrests and feet flat on the ground. The screen before subject demonstrated text command. Each experiment consisted of two parts: first, subject was asked to perform real movement with left or right hand according to the commands, then after a short rest he/she was asked to imagine the same movements after corresponding commands on the screen. In EEG experiment subject was given $\sim$ 15 s to perform one session of real or imaginary movement after text command with 15 s breaks between consecutive commands. Hand movement consisted of repeated tapping of one of four fingers against the thumb, finger order and tapping pace were comfortable for the subject.

For time-frequency analysis of EEG signals continuous wavelet transform (CWT) was used [24], [25]. The CWT is widely used method for time-frequency analysis of complex nonstationary signals with multiple rhythmic components [26]. During recent interdisciplinary studies this method recommended itself as a powerful instrument for analysis of experimental biological data and obtaining essential information about complex dynamics of physiological systems including brain [27].

The CWT is computed as convolution of EEG signal $x(t)$ with wavelet basis function $\varphi_{s,\tau}$:

$$W_n(s,\tau) = \frac{1}{\sqrt{s}} \int_{-\infty}^{\infty} x_n(t) \varphi^*_{s,\tau}(t) dt, \tag{1}$$

where n = 1, 2... N is the number of EEG channel (N = 31) and "*" stands for complex conjugation. Each basis function $\varphi_{s,\tau}$ can be obtained from one function φ_0 called mother wavelet:

$$\varphi_{s,\tau}(t) = \frac{1}{\sqrt{s}} \varphi_0 \left(\frac{t - t_0}{s} \right), \tag{2}$$

where s — time scale responsible for extension/compression of mother wavelet, t_0 — time shift of mother wavelet. Complex Morlet wavelet was used as mother wavelet:

$$\varphi_0(\eta) = \pi^{-\frac{1}{4}} e^{j\omega_0 \eta} e^{-\frac{\eta^2}{2}}, \tag{3}$$

where parameter $\omega_0 = 2\pi$ is the central frequency of Morlet wavelet, $\eta = \frac{t-t_0}{s}$.

Wavelet energy characterize distribution of spectral power in time and in frequency domains and can be computed as

$$E(f,\tau) = |W(f,\tau)|^2 \tag{4}$$

Surface of CWT energy (wavelet spectrum) provides common information about time-frequency structure of the signal, such as length of some pronounced oscillatory patterns and their main frequencies.

Wavelet energy spectrum is commonly analyzed in number of specific frequency bands: delta (2-4 Hz), theta (4-8 Hz), alpha (8-13 Hz) and beta (15-30 Hz). For one particular frequency band F averaged wavelet energy was calculated as:

$$E_F(t) = \frac{1}{\Delta f_F} \int_{f \in f_F} E(f,t) df, \tag{5}$$

The wavelet analysis of EEG recordings was performed with developed C/Cuda software for increasing computation performance [28].

III. Results

In the first part of our work we analyzed fNIRS data — results are illustrated for motor execution (Fig. 1) and for motor imagery (Fig. 2). Distributions of HbO and HbR are presented for the left hemisphere with placements of certain

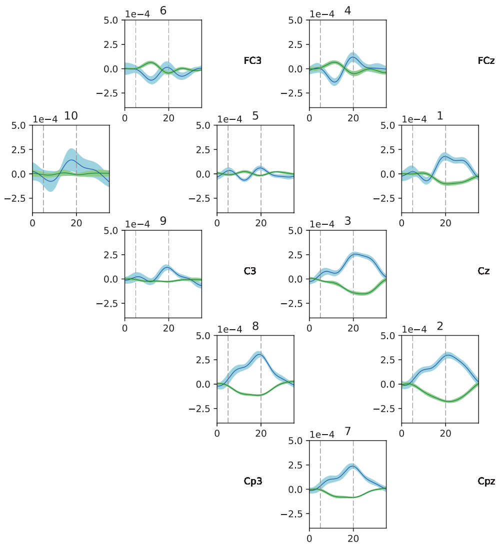

Fig. 1. Distributions (mean and standard error) of HbO (blue) and HbR (green) for right hand motor execution. Distributions provided for fNIRS channels of left hemisphere. Black dotted vertical lines mark the beginning and the end of motor execution. Labels with EEG channel names correspond to approximate placements of these channels.

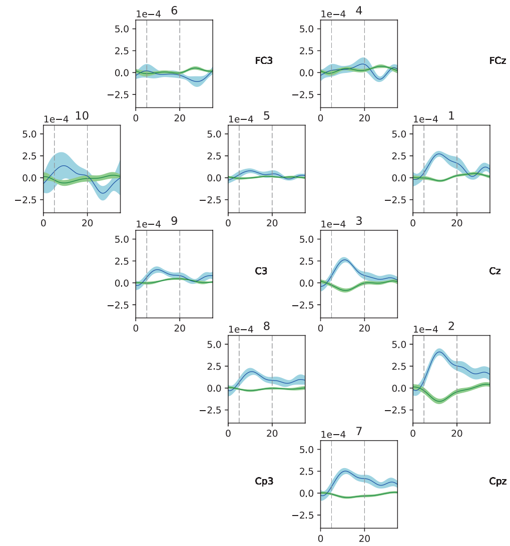

Fig. 2. Distributions (mean and standard error) of HbO (blue) and HbR (green) for right hand motor imagery. Distributions provided for fNIRS channels of left hemisphere. Black dotted vertical lines mark the beginning and the end of motor imagery. Labels with EEG channel names correspond to approximate placements of these channels.

major EEG channels. As one can see, some channels demonstrate dynamics expected from motor activity — increase in level of HbO with corresponding decrease in level of HbR. Channels with pronounced dynamics (for example, 2, 3, 7, 8) are placed near EEG channels C3 and Cp3, that correspond to primary motor cortex. These results are in good agreement with previous studies [11]–[13]. Moreover, this dynamics in symmetric fNIRS channels in the right hemisphere is far less pronounced. All these findings open opportunity to find brain area responsible for motor activity and to distinguish different types of movement according to fNIRS dynamics in the chosen area. However, from Fig. 1 and mostly from Fig. 2 one can see, that mentioned dynamics becomes noticeale only few seconds after the beginning of motor activity. For the purposes of BCI these time intervals may be too long, so one should probably consider other types of brain activity with quicker response to the motor execution/imagery — such as EEG.

In the second part of our work we computed wavelet energy spectra (f, t) along with wavelet energy averaged over alpha (mu) frequency range $E_\alpha(t)$. Fig. 3 demonstrates results obtained for right hand motor execution and motor imagery on EEG channel C3 (left hemisphere). It can be seen that Fig. 3a,b demonstrates notable drop in α-activity even shortly before the start of motor execution. Fig. 3c,d also shows decrase in α-rhythm after motor imagery, however, these changes appear earlier than for fNIRS signals. As diagnostics method EEG alone can be used to distinguish motor activity from background, however, there is no essential difference in such dynamics for left and right hand movement. At the same time, combination of EEG and fNIRS opens new prospects: fNIRS can be used to find cortex areas that are more active during certain motor activity while EEG can be used for faster and more precise detection, which is especially important in case of BCI.

IV. Conclusion

In this paper we performed combined analysis of EEG and fNIRS data acquired during human's motor execution and motor imagery. We performed analysis of EEG signals with help of CWT and analysis of hemodynamics acquired through fNIRS. We found that there are certain features on both EEG and fNIRS signals related to different types of motor activity. We showed that both EEG and fNIRS analysis have own pros and cons in detection of certain types of motor activity, so combination of these two approaches can be used to greater effect.

V. ACKNOWLEDGMENTS

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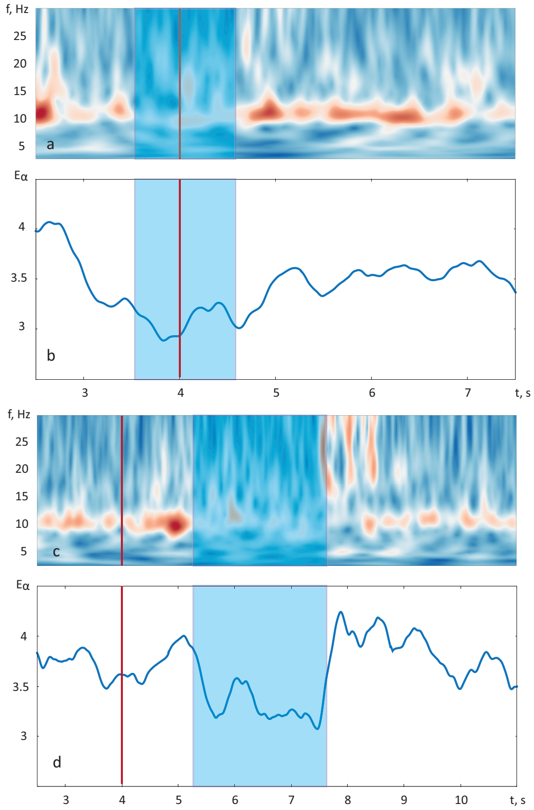

Fig. 3. Results of EEG analysis: wavelet spectra for right hand motor execution (a) and imagery (c), distributions for wavelet energy averaged over α-range for right hand motor execution (b) and imagery (d). Dark red vertical lines mark the start of motor activity. Shaded blue frames mark areas with drop in α-rhythm activity.

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