

# Features of real and imaginary motor activity on EEG and fNIRS signals for neurorehabilitation

Vadim Grubov

*Neuroscience and Cognitive Technology Lab, Center for Technologies in Robotics and Mechatronics Components*  
*Innopolis University*  
Innopolis, Russia  
v.grubov@innopolis.ru

Nikita Frolov

*Neuroscience and Cognitive Technology Lab, Center for Technologies in Robotics and Mechatronics Components*  
*Innopolis University*  
Innopolis, Russia  
n.frolov@innopolis.ru

Elena Pitsik

*Neuroscience and Cognitive Technology Lab, Center for Technologies in Robotics and Mechatronics Components*  
*Innopolis University*  
Innopolis, Russia  
e.pitsik@innopolis.ru

Artem Badarin

*Neuroscience and Cognitive Technology Lab, Center for Technologies in Robotics and Mechatronics Components*  
*Innopolis University*  
Innopolis, Russia  
a.badarin@innopolis.ru

**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 imaginary.

**Keywords** — EEG, fNIRS, real and imaginary motor activity, time-frequency analysis

## I. INTRODUCTION

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 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 [1]. Instead of electrical processes, other sources of information about brain can also be used, for instance, functional near-infrared spectroscopy (fNIRS) [2,3].

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 [4]. Previous studies outlining the similarities between real motor activity and motor imagery [5-7]. 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).

## II. MATERIALS AND METHODS

### A. Experiments

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.

In the first part of the study we recorded electroencephalogram (EEG) - sum of electrical currents generated by a small group of neurons in brain network [8]. For EEG signal recording we used electroencephalograph "Encephalan-EEG-19/26" (Medicom MTD company, Taganrog, Russian Federation). To obtain EEG signals we used "10-10" scheme for EEG electrode placement with 31 EEG channels. Before EEG recording scalp was treated with the abrasive "NuPrep" gel in order to increase skin conductivity, then cup adhesive Ag/AgCl electrodes were noninvasively placed on scalp with help of "Ten20" paste. The impedance of electrodes was monitored during the experimental procedure with typical values of 2-5 kΩ. The ground electrode N was located above the forehead near the Fpz electrode location and two referent electrodes were located on the earlobes. The EEG signals were filtered by band-pass filter (high-pass at 0.016 Hz and low-pass at 100-Hz) and by 50-Hz notch filter. Time resolution of the recorded EEG signals was 250 Hz.

In the second part we used functional near-infrared spectroscopy (fNIRS) - a noninvasive, relatively low-cost, portable optical brain-imaging technique [9]. 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 [10]. 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 complementary to information provided by EEG analysis.

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  $\sim 900$  nm, that can pass through skin, bone, and water, but are highly absorbed by HbO and HbR correspondingly [11]. 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 [12]. 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  $\sim 7.8$  Hz.

Basic experimental design was the same for EEG and fNIRS parts: 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 and 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  $\sim 4$  s to perform one real movement after text command with 4-6 s breaks between consecutive command. Time interval for imaginary movement was  $\sim 7$  s with 6-8 s breaks. In fNIRS experiment subject performed or imagined movement for the same time intervals of 15 s with 15 s breaks between them. Hand movement consisted of curling the fingers towards the palm as if squeezing an imaginary ball. In both experiments subject performed 20 real and 20 imaginary movement for each hand.

### B. Data analysis

For time-frequency analysis of EEG signals we used continuous wavelet transform (CWT), which has recently become a very popular technique for studying dynamics of neurophysiological brain activity [13-15]. CWT is a convolution of EEG signal  $x(t)$  with basic function  $\psi(\eta)$  as

$$W_n(f, t) = \sqrt{f} \int_{-\infty}^{+\infty} x_n(t) \psi^*(f, t) dt, \quad (1)$$

where  $n = 1, 2 \dots N$  is the number of EEG channel ( $N = 31$ ) and '\*' stands for complex conjugation. As mother wavelet of CWT we used the complex Morlet wavelet

$$\psi(\eta) = \frac{1}{\sqrt{\pi}} e^{j\omega_0\eta} e^{-\eta^2/2} \quad (2)$$

where  $\eta = f(t - t_0)$  and  $\omega_0 = 2\pi$  is the wavelet central frequency.

Wavelet energy spectrum ( $E^n(f, t) = \sqrt{W_n^2(f, t)}$  where  $n$  is number of EEG channels) provides information about time-frequency structure of the signal. We also analyzed wavelet energy in alpha frequency range (8-13 Hz) For this

particular frequency band averaged wavelet energy was calculated as:

$$E_\alpha^n(t) = \frac{1}{\Delta f} \int_{f \in f_\alpha} E^n(f, t) df \quad (3)$$

### III. RESULTS

We processed EEG signals with CWT and computed wavelet energy spectra  $E^n(f, t)$  along with wavelet energy averaged over alpha frequency range  $E_\alpha^n(t)$ . Fig. 1 demonstrate results for real movements of left and right hands on EEG channel C3.

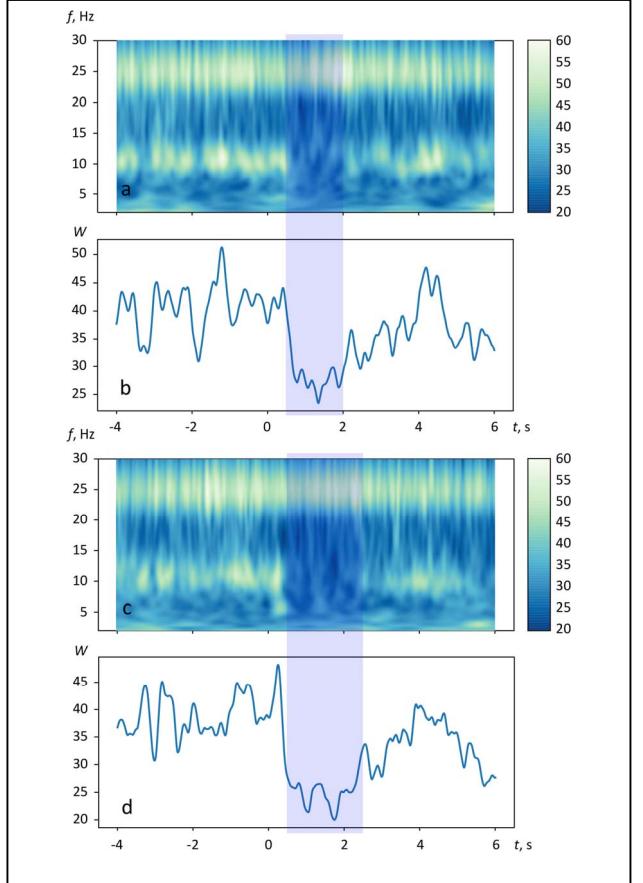


Fig. 1. Wavelet spectra for left (a) and right (c) hand movement, distributions of averaged wavelet energy for left (b) and right (d) hand movement

As one can see from Fig. 1 left and right hand movements are accompanied by pronounced decrease of wavelet energy level in alpha frequency band. This can be used to distinguish movement from background activity, however, there is no essential difference in such dynamics for left and right hand movement.

Results from fNIRS experiment are illustrated on Fig. 2 and 3. As one can see, increase in level of HbO with corresponding decrease of HbR mark each movement, real or imaginary. Moreover, this dynamics is more pronounced in right hemisphere for left hand and in left hemisphere for right hand, which opens opportunity to distinguish different types of movement. These results can be used in further research with synchronous recording of EEG and fNIRS in one experiment.

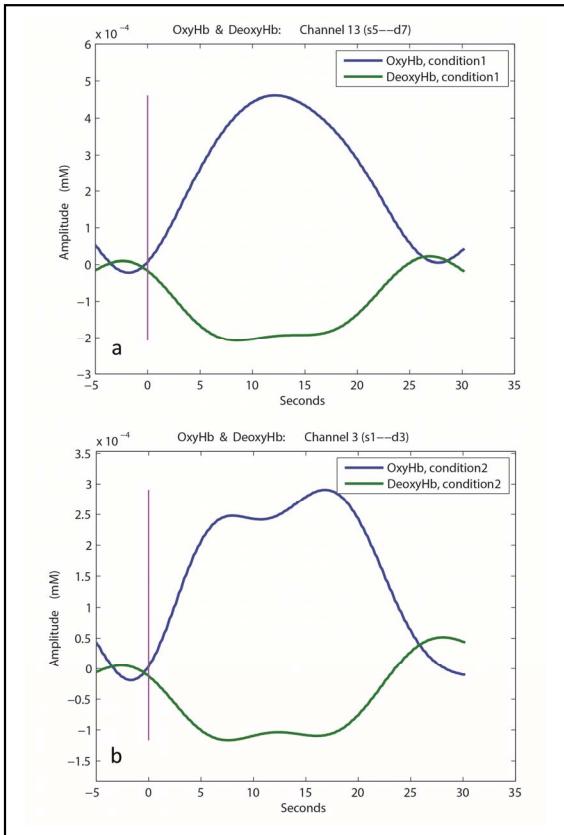


Fig. 2. Distributions of HbO (red) and HbR (blue) for real left hand movement in right hemisphere (a) and real right hand movement in left hemisphere

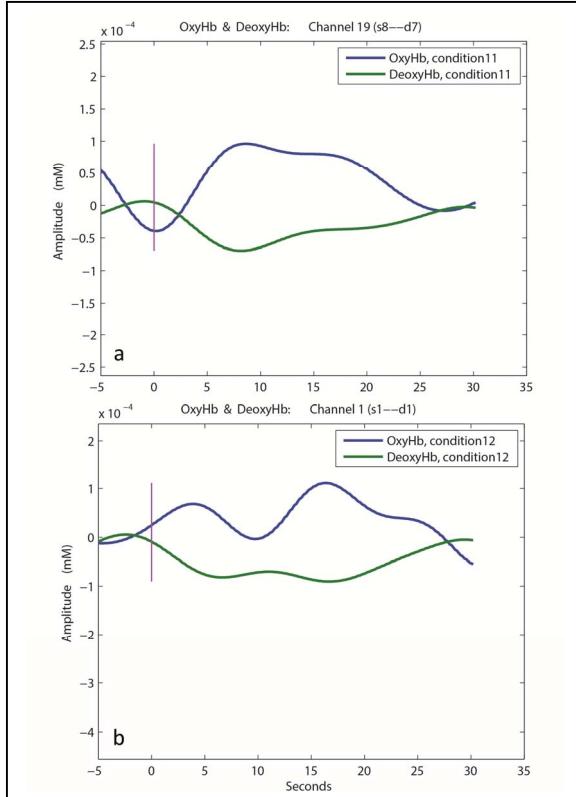


Fig. 3. Distributions of HbO (red) and HbR (blue) for imaginary left hand movement in right hemisphere (a) and imaginary right hand movement in left hemisphere (b)

## ACKNOWLEDGMENT

This work has been supported by the Center for Technologies in Robotics and Mechatronics Components (Innopolis University).

## REFERENCES

- [1] J. R. Wolpaw, E. W. Wolpaw, Brain-computer interfaces: principles and practice. New York: Oxford University Press, 2012 .
- [2] A. Abdalmalak et al, "Single-session communication with a locked-in patient by functional near-infrared spectroscopy," *Neurophotonics*, vol. 4(4), pp. 040501, 2017.
- [3] A. Abdalmalak et al, "Can time-resolved NIRS provide the sensitivity to detect brain activity during motor imagery consistently?" *Biomed Opt Express*, vol. 8, pp 2162-2172, 2017.
- [4] M. Jeannerod, "Mental imagery in the motor context," *Neuropsychologia*, vol. 33, no. 11, pp. 1419–1432, 1995.
- [5] J. Munzert, B. Lorey, and K. Zentgraf, "Cognitive motor processes: the role of motor imagery in the study of motor representations," *Brain Research Reviews*, vol. 60, no. 2, pp. 306–326, 2009.
- [6] N. Sharma, P. S. Jones, T. A. Carpenter, and J.-C. Baron, "Mapping the involvement of BA 4a and 4p during Motor Imagery," *NeuroImage*, vol. 41, no. 1, pp. 92–99, 2008.
- [7] A. Solodkin, P. Hlustik, E. E. Chen, and S. L. Small, "Fine modulation in network activation during motor execution and motor imagery," *Cerebral Cortex*, vol. 14, no. 11, pp. 1246–1255, 2004.
- [8] E. Niedermeyer, L. S. Fernando, *Electroencephalography: Basic Principles, Clinical Applications, and Related Fields*, Lippincott Williams & Wilkins, 2004.
- [9] H. Ayaz, B. Onaral, K. Izzetoglu, P. A. Shewokis, R. Mckendrick, and R. Parasuraman, "Continuous monitoring of brain dynamics with functional near infrared spectroscopy as a tool for neuroergonomic research: empirical examples and a technological development," *Frontiers in Human Neuroscience*, vol. 7, article 871, 2013.
- [10] A. Villringer and B. Chance, "Non-invasive optical spectroscopy and imaging of human brain function," *Trends in Neurosciences*, vol. 20, no. 10, pp. 435–442, 1997.
- [11] H. Ayaz, P. A. Shewokis, A. Curtin, M. Izzetoglu, K. Izzetoglu, and B. Onaral, "Using MazeSuite and functional near infrared spectroscopy to study learning in spatial navigation," *Journal of Visualized Experiments*, no. 56, pp. 1–12, 2011.
- [12] M. Cope, *The Development of a near Infrared Spectroscopy System and Its Application for Non Invasive Monitoring of Cerebral Blood and Tissue Oxygenation in the Newborn Infants*, University of London, London, UK, 1991.
- [13] A. Hramov et al, *Wavelets in neuroscience*, Springer Berlin Heidelberg, 2015.
- [14] V. A. Maksimenko, S. A. Kurkin, E. N. Pitsik, V. Y. Musatov, A. E. Runnova, T. Y. Efremova, A. E. Hramov, A. N. Pisarchik, "Artificial neural network classification of motor-related eeg: An increase in classification accuracy by reducing signal complexity," *Complexity*, V. 2018, no. 9385947, 2018.
- [15] P. Chholak, G. Niso, V.A. Maksimenko, S.A. Kurkin, N.S. Frolov, E.N. Pitsik, A.E. Hramov, A.N. Pisarchik, "Visual and kinesthetic modes affect motor imagery classification in untrained subjects," *Scientific reports*, V. 9, no. 1, p. 9838, 2019.