Classification of hand-related real and imaginary motor activity with fNIRS

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***Abstract*—In the present work we studied blood oxygenation/deoxygenation spatial dynamics related to real and imaginary motor activity using functional near-infrared spectroscopy (fNIRS). We revealed biomarkers based on pronounced hemispheric lateralization of hemodynamical response in the motor cortex during motor activity. We used these markers to design a sensing method for classification of movement's type. The accuracy of real movements classification was close to 100%, while for imaginary movements it was lower but still quite high (about 90%). The proposed system can find application, for example, in neurorehabilitation after severe brain injuries, including traumas and strokes.**

***Index Terms*—brain activity, functional near-infrared spectroscopy (fNIRS), real and imaginary motor activity**

I. Introduction

It is well-known, that in nonlinear dynamics brain considered as a very complex dynamical system with huge number of elements — neurons [1]. The neurons are connected by synapses and thus form a complex network with nodes and links. Features of time-spatial activity of this neural network provide important information about the current state of the nervous system and cognitive brain ability [2]–[5]. Particular brain states can be associated with specific activity such as motor brain activity during either real or imaginary movement [6]–[11].

Studies on brain activity related to real motor activity and motor imagery of different limbs can be essential not only for basic research in neuroscience, but also for applications in engineering and medicine. For example, this knowledge can be used in development of brain-computer interfaces (BCIs). One of the goals of such systems is to improve the quality of life for post-traumatic and post-stroke patients and to aid in neurorehabilitation [12]–[14] or to control prostheses and exoskeletons [15]. One of the basic BCI functions is online detection of specific features in analyzed signals of brain activity. Common forms of brain activity used in BCI are represented by electroencephalography (EEG) [16] and magnetoencephalography (MEG) [17]. However, some other techniques for acquiring information about brain state can be used in BCI and provide their own benefits.

Functional near-infrared spectroscopy (fNIRS) [18], [19] is one of such techniques. It is a powerful tool of noninvasive optical imaging, that successfully used in BCI for registration of brain activity with further control command formation [20]–[22]. Benefit of control commands of this type is their resistance to influence by any muscular activity [23]. Studies on motor imagery are also very important for designing rehabilitation BCI [17], [24]. Motor imagery is a mental process by which a person simulates a given action with no real motor activity. Some researchers treat motor imagery as a conscious application of unconscious preparation for real motor activity [25]. By now it is known that real and imaginary motor activity share some common features [26]–[28]. One of such features is the similarity of cortical layout in the primary motor cortex M1 between motor execution and motor imagery, which is quite important for the BCI development.

In this paper, we analyzed blood oxygenation/deoxygenation spatial dynamics related to real and imaginary motor activity using fNIRS. In particular, we extracted specific features of the fNIRS signals related to different types of motor activity, which can be used in BCIs. We also proposed an universal method for classification of fNIRS trials obtained during motor imagery and developed a sensor of motor activity with possibility to be used in neurorehabilitation systems.

II. Materials and Methods

A. Participants and Experimental setup

Twelve healthy volunteers in the age of 22–38 year participated in the experiment. All participants were right-handed, amateur practitioners of physical exercises, non-smokers, without diagnosed diseases of the musculoskeletal system. All volunteers signed written consent that they were informed about the design of the experiment with its possible inconveniences and limitations. The experiment was conducted in accordance with Helsinki Declaration 1964 and was approved by the local Ethics Committee. All experimental works were carried out

President's Program (Project MD-1921.2020.9)

978-1-7281-7286-6/20/$31.00 ©2020 IEEE

in the Neuroscience and Cognitive Technology Lab of the Innopolis University.

The experiment was designed to record a hemodynamic neuronal response in the motor cortex using fNIRS which records fast changes in the brain activity. The fNIRS signals were acquired by the NIRScout device manufactured by the NIRx Company (Germany). The NIRScout system used 8 sources and 8 detectors placed on the subject's scalp in the primary motor cortex area (M1) to record hemodynamic response data with 7.8125-Hz resolution. Each pair "source–detector". that were placed close enough to each other (at about 2-3 cm), formed a fNIRS channel (a total of 20 channels).

The experiment was performed as follows. The subjects were sitting in a comfortable chair while performing motor activity or motor imagery related to left and right hands. Each action was performed after the corresponding text command demonstrated on a computer monitor that was placed in front of the subject's eyes at a distance of 70–80 cm. Each experiment included two sessions. In the first session, the subject performed real movements with left or right hand according to the commands on the screen. Then, after a short break, in the second session the subject imagined the same type of movement according to the commands on the screen. Each fNIRS trial in each session consisted of the command presentation indicating the required type of motor activity (the subject was given 15 s to perform movement during this command presentation) and the rest interval (15 s from the end of motor activity till the next command). There were 10 trials for each type of motor activity.

Hand movement consisted of repeated bending/unbending of fingers to the center of the palm (similar to the clenching of imaginary ball). The repeated movements were performed at the pace comfortable for the subject.

B. Data preprocessing

Laser light with two wavelengths, $\lambda_1 = 785\,\text{nm}$ and $\lambda_2 = 850\,\text{nm}$, was used in the fNIRS device. Light with these characteristics can pass through most types of tissues in body, but is highly absorbed in blood by oxyhemoglobin and deoxyhemoglobin, respectively [29].

Raw fNIRS data need to be preprocessed in order to be used as indicator of changes in oxygenation of the tissues. Oxyhemoglobin and deoxyhemoglobin have different light absorption, so we used modified Beer–Lambert law to calculate changes in the reflected dual-wavelength light [30]. We also introduced characteristic H, which reflects relative changes in oxyhemoglobin and deoxyhemoglobin.

The fNIRS data acquisition and preprocessing were performed with software NIRScout. As a part of preprocessing we applied the 0.01–0.1 Hz band-pass filter to the raw fNIRS signals. It is known that band-pass filtering is enough to remove most physiological artifacts such as Mayer wave (with a typical frequency close to 0.1 Hz), respiration (close to 0.25 Hz), and heartbeat (close to 1 Hz) [31].

For the further analysis 35-s long trials of fNIRS data were formed. Each trial included 5-s preparation before the text command, 15-s motor activity, and 15-s rest interval. The 5-s interval at the beginning of each trial was used for baseline correction. Namely, the distribution of HbO/HbR was averaged over these 5 s and the obtained value was subtracted from the corresponding trial.

III. Results

A. Data analysis

The characteristic H^i ($i = 1, \ldots, 20$ is the fNIRS channel) provides information about HbO/HbR dynamics. However, to compare significance of such dynamics in different areas of motor cortex we introduced a new characteristic $dH^{i,j}$.

First, we calculated the value of $\langle H^i \rangle_T$ as H^i averaged for each fNIRS channel, separately for HbO and HbR, across time interval $T \in (5, 20)$ s corresponding to real or imaginary motor activity:

$$\langle H^i \rangle_T = \int_T \Delta H^i \, dt. \tag{1}$$

In the previous papers [32], [33], we have introduced the measure of connectivity based on the reconstruction of functional links between neuronal ensembles in different frequency bands by comparing spectral components of the EEG signals belonging to these bands. Here, we extended this approach to the time domain for analyzing the restoration of connectivity by similarity of hemodynamic responses in different areas of the motor cortex. This allows us to identify the cortical region in M1 with most similar activity for further classification of motor execution events.

According to the described approach, we calculated matrices $dH^{i,j}$ of the difference between $\langle H \rangle_T$ for all fNIRS channels i and j ($i, j = 1, \ldots, 20$) for each type of motor activity (real and imaginary) for both HbO and HbR as:

$$dH^{i,j} = \langle H^i \rangle_T - \langle H^j \rangle_T. \tag{2}$$

It is known [34] that execution of real movement is accompanied by increase of oxyhemoglobin (H_{HbO}) and simultaneous decrease of deoxyhemoglobin (H_{HbR}) in M1. Therefore, in the resulting matrices $dH^{i,j}$ we left only absolute values of $dH^{i,j} > 0$ for HbO and $dH^{i,j} < 0$ for HbR. As the result we constructed the distributions $N(dH^{i,j})$ of $dH^{i,j}$ for each 20×20 matrix obtained for HBO and HbR in the case of left/right real and imaginary movements. These diagrams are illustrated by Figure 1a,b.

According to the obtained distributions $N(dH^{i,j})$ we introduced cumulative distribution functions $F_{dH^{i,j}}(h) = P(dH^{i,j} \leq h)$ which yield the probability for $dH^{i,j}$ to be smaller than h. The fourth quartile of the $F(h)$ distribution is the value of $h \geq 0.75$. The corresponding cumulative distributions are shown in Figure 1a,b by red curves, while dashed vertical lines indicate the border of the fourth quartile. We only considered $d\bar{H}^{i,j}$ values that fall into the fourth quartile of distributions ($F(\bar{H}^{i,j}) \geq 0.75$) because the resulting values of $d\bar{H}^{i,j}$ were the most significant and thus can be used to find fNIRS channels suitable for the classifier.

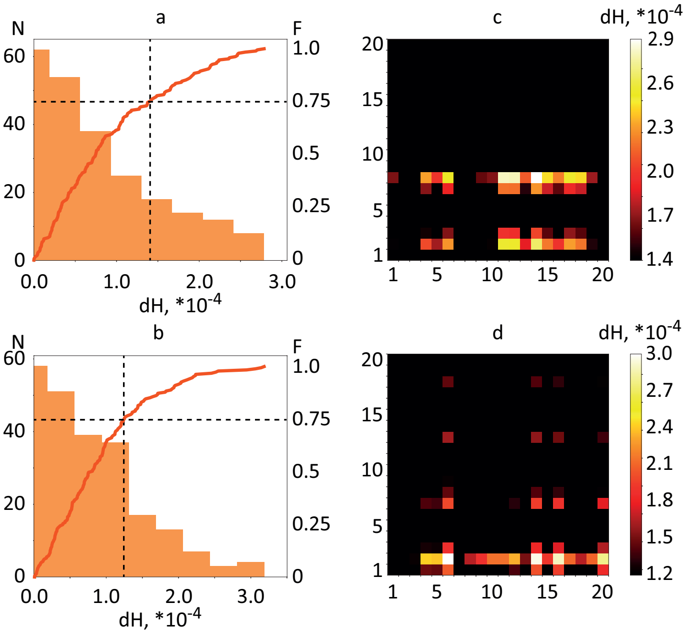

Fig. 1. Distribution of $|dH^{i,j}|$ values and cumulative distribution function F for right-handed motor activity: (**a**) HbO and (**b**) HbR. The black dashed lines indicate the border of the fourth quartile (75%) of the distributions. Distributions of dH across fNIRS channels for right-handed motor activity: (**c**) HbO and (**d**) HbR.

For better illustration of laterality Figure 1c,d shows distributions of dH across fNIRS channels for right-handed motor activity: it is clear, that values of dH are much higher for channels in the left hemisphere (channels $1-10$).

B. Classification algorithm

Obtained results allowed us to propose the online algorithm for binary classification of brain activity during real and imagery motor executions. The proposed algorithm for processing fNIRS data contained the following main steps.

1) For each considered channel i and type of motor activity (right/left hand, execution/imagery) we subtracted spatial oxyhemoglobin (HbO) (H^i_{HbO}) and deoxyhemoglobin (HbR) (H^i_{HbR}) distributions for the right hemisphere (H^j_R, fNIRS channels j of interest from right hemisphere) from the corresponding distribution for the left hemisphere (H^i_L, symmetrical channels i from left hemisphere). We calculated differences for individual symmetrical channels in the left and right hemispheres as

$$\Delta H^i_{\mathrm{HbO}} = H^i_{\mathrm{HbO},\,L} - H^j_{\mathrm{HbO},\,R}, \tag{3}$$

$$\Delta H^i_{\mathrm{HbR}} = H^i_{\mathrm{HbR},\,L} - H^j_{\mathrm{HbR},\,R}. \tag{4}$$

2) Then, we averaged $\Delta H^i_{\mathrm{HbO}}$ and $\Delta H^i_{\mathrm{HbOR}}$ over the time interval corresponding to motor activity $T \in (5, 20)$ s to find $\langle \Delta H^i_{\mathrm{HbO}} \rangle_T$ and $\langle \Delta H^i_{\mathrm{HbO}} \rangle_T$ as

$$\langle \Delta H^i_{\mathrm{HbO}} \rangle_T = \int\limits_T \Delta H^i_{\mathrm{HbO}}\, dt, \tag{5}$$

$$\langle \Delta H^i_{\mathrm{HbR}} \rangle_T = \int\limits_T \Delta H^i_{\mathrm{HbR}}\, dt. \tag{6}$$

3) For each separate fNIRS signal trial, we calculated characteristics C_R and C_L taking into account the following criteria for each considered symmetric fNIRS channels in the left and right hemispheres.
   (i) If $\langle \Delta H^i_{\mathrm{HbO}} \rangle_T > 0$ and $\langle \Delta H^i_{\mathrm{HbR}} \rangle_T < 0$ was true for one of the channels i, then $C_R := C_R + 1$.
   (ii) If $\langle \Delta H^i_{\mathrm{HbO}} \rangle_T < 0$ and $\langle \Delta H^i_{\mathrm{HbR}} \rangle_T > 0$ was true for one of the channels i, then $C_L := C_L + 1$.
4) Finally, we made a decision according to the following criteria.
   (i) If $C_R > C_L$, then right-hand (real or imaginary) motor activity takes place.
   (ii) If $C_R < C_L$, then left-hand (real or imaginary) activity takes place.
   (iii) If $C_R = C_L$, then the type of activity is uncertain.

We applied the classification algorithm in our fNIRS-based experimental system for online classification of real and imaginary motor actions. We used the proposed classifier with six fNIRS channels $i = \{2, 7, 8\}$ in the left hemisphere and $j = \{12, 17, 18\}$ symmetric channels in the right hemisphere. Notably, in the majority of cases the type of motor action (both real and imagery) in all subjects was correctly identified by the data from only three fNIRS channels.

IV. Conclusion

In this paper, we have carried out the analysis of fNIRS data acquired during real and imaginary movements. Distinct spatial dynamics in the motor cortex when performing motor actions (real or imaginary) with the left or right hand exhibited pronounced laterality between two hemispheres. This allowed us to reveal hemodynamic biomarkers for classification of the type of movement. The proposed fNIRS-based sensor provided close to 100% recognition accuracy in the detection of real movements, while the classification accuracy of motor imagery is a little worse and reached 90%.

The important advantage of the proposed method is the possibility to efficiently classify different types of movement, both real and imaginary, without recalculation of the system parameters. This essential feature of the developed sensor results from pronounced laterality of the hemodynamic brain response to motor activity.

The knowledge of the hemodynamic behavior in the motor cortex during real and imaginary motor activity along with approaches for its detection can be helpful not only for fundamental studies on human motor-related tasks but also for the development of fNIRS-based BCIs.

Acknowledgment

This work was supported by President's Program (Project MD-1921.2020.9).

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