Study of cortical characteristics in operators of BCI with tactile feedback

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***Abstract*— A Brain-Computer Interface (BCI) is a technology that enables the exchange of information between the brain and external devices by processing electrical signals from the cerebral hemispheres. This technology can be applied in the development of neurotrainers for individuals who have had a stroke. In this work, we examined the classification accuracy of motor imagery-based Brain-Computer Interfaces with tactile feedback and assessed corticospinal excitability. The study has shown that the EEG signal classification accuracy results were compared between two BCI variants: one without feedback and one with tactile feedback. The average results across all participants showed no statistically significant difference, with accuracy rates of 63.04% for BCI without feedback and 65.58% for BCI with tactile feedback. We found that when participants engaged in imagined movements, there was a statistically significant increase in MEP amplitude compared to a "rest" state, regardless of their prior training. This suggests an increase in corticospinal excitability during imagined movements.**

***Keywords*— BCI, TMS, EEG, nTMS, motor imaging.**

I. INTRODUCTION

Stroke's aftermath frequently involves impaired motor functions, resulting in challenges when executing routine limb movements. These movement disturbances stem from cerebral cortex damage and disruption of neural connections within the central pyramidal pathways [1]. The journey to restore motor skills post-stroke is a demanding and time-intensive endeavor, demanding both medical intervention and the patient's dedication. Nonetheless, the recovery of limb control remains attainable. Standard stroke neurorehabilitation typically involves therapeutic physical exercises and kinesitherapy, capitalizing on sensory input during motor tasks to rebuild connections between unaffected brain regions [2]. Through limb exercises, synaptic reorganization within the cortex takes place, reactivating dormant neurons and expanding the cortical areas neighboring inactive ones. Despite the effectiveness of these methods in partially restoring movement, many stroke survivors continue to grapple with limitations. Traditional rehabilitation approaches often fall short of completely reinstating motor control, compelling researchers to explore alternative avenues. Motor-imagery-based brain-computer interfaces

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(BCIs) have garnered attention recently [3,4,5]. These interfaces allow for the incorporation of diverse feedback mechanisms and can be coupled with upper and lower limb exoskeletons. The extent of control that an individual can exert over a BCI system directly influences the recovery process [6,7]. The integration of transcranial magnetic stimulation (TMS) into motor-imagery BCIs holds promise in establishing a unified and highly effective post-stroke rehabilitation methodology.

II. METHODS

A. *Participants*

Seven healthy volunteers (3 females and 4 males) aged 18-27 years (mean±standard deviation 22.7±2.7) took part in the study. All participants had no prior experience with EEG and were right-handed (mean±standard deviation 0.87±0.14 points on the Edinburgh Handedness Inventory)[8]. All participants provided informed consent to participate in the research. The research protocol was approved by the ethics committee of the Lobachevsky State University of Nizhny Novgorod, Institute of Biology and Biomedicine.

B. *EEG Registration and Classification*

EEG recordings were conducted using the NVX52 electroencephalograph (Medical Computer Systems LLC, Russia) with 29 Cl/Ag electrodes (F1, Fz, F2, FC5, FC3, FC1, FCz, FC2, FC4, FC6, C5, C3, C1, Cz, C2, C4, C6, CP5, CP3, CP1, CPz, CP2, CP4, CP6, P3, P1, Pz, P2, P4) placed according to the 10-10 system. Combined earlobe electrodes were used as a reference, and the grounding electrode was positioned on the forehead. The contact impedance for all electrodes did not exceed 15 kΩ. The EEG signal was digitized at a sampling rate of 1000 Hz and filtered in the frequency range of 1-30 Hz with a 50 Hz Notch filter.

Classification was performed using linear discriminant analysis. EEG classification and feedback presentation to the participants were conducted in cycles of 700 ms. The EEG signal acquired during the first 500 ms was used for classification, and if necessary, feedback was provided to the participants during the subsequent 200 ms.

The duration of command presentation at all stages of the experiment was 5 seconds (7 cycles of classification and feedback), with a 3-second gray background presented to the participants for rest between them. Mental tasks included imagined movements of the left and right hands and a "rest" task in which participants were required to maintain a state of wakeful rest. The "rest" command was represented by a fixation cross in the center of the screen, while left and right hand motor imagery tasks were indicated by arrows to the left or right of the fixation cross, respectively. Each test session consisted of 30 command presentations, with 10 for each mental task. The sequence of command presentations was randomized, and participants were allowed to rest between tests as needed.

C. *Experimental design*

The experiment consisted of four sessions, each conducted on a separate experimental day.

The first experimental session involved training the subjects in the technique of imagination movements. Before the training began, the subjects underwent a test for manual asymmetry. The activation movement for all subjects involved clenching the hand into a fist, with an emphasis on tactile sensations. The training consisted of three sequential stages: real hand movements, quasi-movements (muscle tension not visually observed), and imagination of movements.

The subjects underwent a magnetic resonance imaging (MRI) procedure. Digital MRI data were used to construct a 3D model of the subject's head using the navigation system of the transcranial magnetic stimulator - Visor2 (TMS Navigator Value, manufactured by Localite GmbH, Germany) and Neurosoft software. The resulting model was then used for navigational transcranial magnetic stimulation (nTMS, "Neuro-MS/D" (Research), manufactured in Ivanovo, Russia, by Neurosoft) to assess the excitability of the brain cortex after working with imagined movements.

The second experimental session included three tests without feedback presentation and the procedure for assessing the excitability of the motor cortex of the brain after working with imagined movements using nTMS. Using the navigation program and single stimuli with an 8-shaped TMS coil, the cortical motor representation of the short thumb flexor muscle (Musculus flexor pollicis brevis) was determined. Subsequently, the motor response threshold was calculated as the stimulation power required for a pronounced motor response in 50% of stimuli (five out of ten stimulations). Further stimulation was conducted at 115 - 120% above the motor response threshold. Electromyography (EMG) was recorded over the thumb flexor muscle. The "Neuron-Spectrum-5" (LLC "Neurosoft," Russia) was used for EMG recording, and the "Neuron-Spectrum.NET" software was used to measure the amplitude of motor-evoked potentials (MEPs) from peak to peak.

After three test recordings of BCI working, a procedure for measuring the excitability of the motor cortex in a resting state (absence of ideomotor movements) followed. Three recordings were conducted, each comprising 60 stimulations of a functional area at the motor cortex over a duration of 2 minutes. Subjects were given rest time between recordings. Subsequently, the excitability of the motor cortex during the imagination of movements with the dominant hand (based on the Edinburgh Handedness Inventory) was determined. Again, three recordings of 60 stimulations each were conducted. For further analysis, the average amplitude of Motor-Evoked Potentials (MEPs) obtained during imagined movements was normalized to the average MEP amplitude at rest.

In the third and fourth experimental sessions, tactile feedback was provided to the subjects during BCI tests. This feedback was implemented using vibration motors (flat Linear Resonance Actuators (LRAs), 3V, 10mm diameter, operating at 500 Hz), which were placed on the forearms of both the right and left hands and on the back of the neck. These vibrations signaled the successful recognition of EEG patterns during the imagination of movements with the right hand, left hand, and the "rest" task, respectively. The vibration motors were secured to the skin using tapes. To confirm the correctly classified state, a vibration signal lasting 200 ms was delivered in response to the presented command.

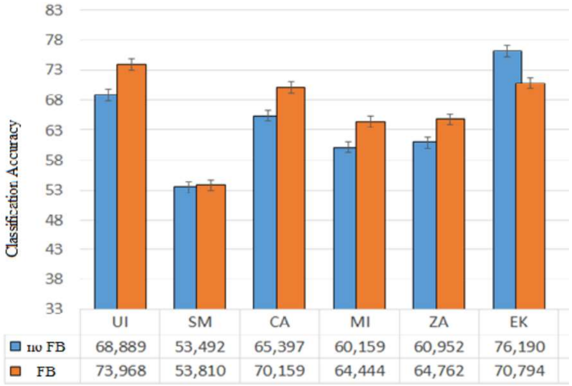
The third session served as a control to assess the influence of vibrotactile stimulation on the degree of sensorimotor rhythm desynchronization and corticospinal excitability. Subjects underwent a procedure similar to working with BCI but were instructed to maintain a state of calm wakefulness regardless of the given command. During this session, the subjects received vibrotactile stimulation identical to the 100% recognition level achieved by the classifier. Subsequently, motor cortex excitability was assessed using nTMS.

The fourth session consisted of three BCI tests with tactile feedback and the assessment of motor cortex excitability after working with BCI using nTMS.

III. RESULTS

We conducted a study to assess the classification accuracy and corticospinal excitability during motor-imagery-based BCI with tactile feedback. Classification accuracy was measured during BCI tasks, while corticospinal excitability was evaluated based on the amplitude of motor-evoked potentials half an hour after subjects completed their work with BCI. The contribution of vibrotactile stimulation to changes in corticospinal excitability was assessed by comparing it with control measurements during passive vibrotactile stimulation in the absence of imagined movements.

The results of EEG signal classification accuracy were compared between two variants of BCI: without feedback and with tactile feedback. The averaged results across all subjects did not demonstrate a statistically significant difference and were 63.04±0.92% (mean±standard error) for BCI without feedback and 65.578±0.89% for BCI with tactile feedback. Figure 1 shows the individual results of each subject. It's worth noting that all subjects achieved classification accuracy above chance level (33% for three commands).



	UI	SM	CA	MI	ZA	EK
🟦 no FB	68,889	53,492	65,397	60,159	60,952	76,190
🟧 FB	73,968	53,810	70,159	64,444	64,762	70,794

Fig. 1. EEG Classification Accuracy for Each Subject. The lower boundary of the graph represents 33% - the probability of random classifier activation. "FB" stands for tactile feedback. The vertical segments indicate the magnitude of the mean error. Below the histogram, a table of results and subject codes is provided.

Within the scope of this study, the goal was to investigate changes in the excitability of the motor cortex in subjects who performed ideomotor movements, depending on their prior training: working within the brain-computer interface loop without feedback, with vibrotactile feedback, and after passive vibrotactile stimulation without imagined movements. When subjects engaged in imagined movements, a statistically significant increase in Motor-Evoked Potentials amplitude was observed compared to the "rest" state after all types of training: working within the BCI loop without feedback, with vibrotactile feedback, and after passive vibrotactile stimulation without imagined movements. This indicates an increase in corticospinal excitability in subjects when they performed imagined movements, regardless of the type of prior training. Figure 2 presents individual MEP results for each subject. Four of the subjects showed significantly higher MEP amplitudes after working within the BCI loop with feedback compared to working with the BCI without feedback. Additionally, in all subjects, MEP amplitudes were higher after training with passive vibrotactile stimulation than after working with the BCI without feedback.

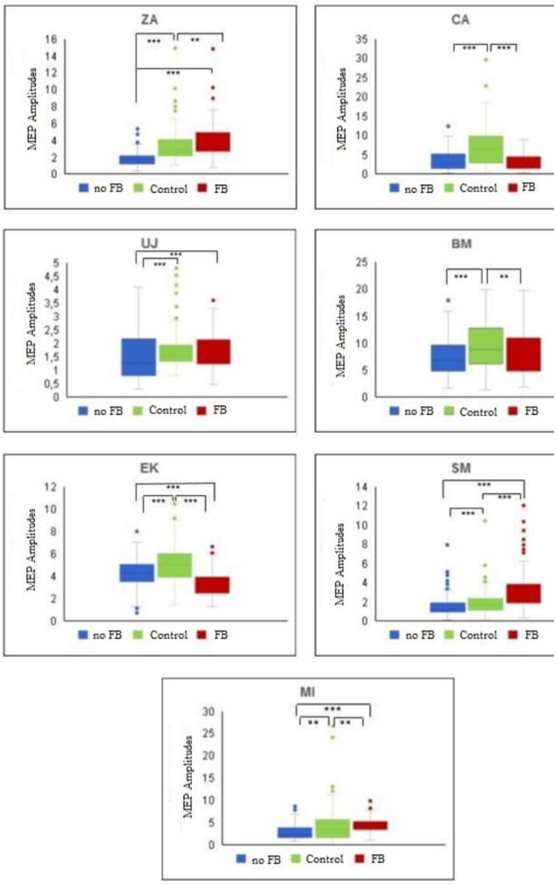


Fig. 2 Comparison of Based on the Type of Prior Training for Each Subject. In the figure, rectangles represent the median (horizontal line) and the interquartile range; vertical lines represent the maximum and minimum values (excluding outliers); individual points represent outliers (values that fall outside 1.5 times the interquartile range from the nearest quartile). ** - $p < 0.01$; *** - $p < 0.001$.

IV. DISCUSSION

In this work, we examined the classification accuracy of motor imagery-based Brain-Computer Interfaces (BCIs) with tactile feedback and assessed corticospinal excitability. We measured classification accuracy during BCI tasks and evaluated corticospinal excitability by looking at the amplitude of motor-evoked potentials (MEPs) after participants completed their BCI tasks. The EEG signal classification accuracy results were compared between two BCI variants: one without feedback and one with tactile feedback. The average results across all participants showed no statistically significant difference, with accuracy rates of 63.04% for BCI without feedback and 65.58% for BCI with tactile feedback.

We found that when participants engaged in imagined movements, there was a statistically significant increase in MEP amplitude compared to a "rest" state, regardless of their prior training. This suggests an increase in corticospinal excitability during imagined movements. Notably, four subjects exhibited significantly higher MEP amplitudes after working with the BCI loop with feedback compared to BCI without feedback. Additionally, in all subjects, MEP amplitudes were higher after training with passive vibrotactile stimulation than after working with BCI without feedback.

Overall, the study indicates that tactile feedback did not significantly affect classification accuracy in motor imagery-based BCIs, but there was a consistent increase in corticospinal excitability during imagined movements, regardless of feedback or prior training.

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