Original article

Reprint

Dynamics of motor imagery skill formation using a brain – computer interface with multimodal feedback

Artem A. Badarin [1], Vladimir M. Antipov [1], Oleg V.Piljugin [2], Mikhail Yu. Novikov [1], Anton R. Kiselev [1] ✉, Oksana M.Drapkina [1]
✉ kiselev@gnicpm.ru

[1]National Medical Research Center for Therapy andpreventive Medicine, Moscow, Russia
[2]Immanuel Kant Baltic Federal University, Kaliningrad, Russia

Received 11 November 2025, Accepted 11 December 2025

Abstract:
Objective: to assess the dynamic of motor imagery skill formation while using brain-computer interface (BCI) with visual and vibrotactile biofeedback.
Material and methods. The pilot study included 10 healthy volunteers aged 29–34 years. All participants were right-handed. Over a five-day protocol, two feedback modalities were employed: visual and vibrotactile. Detection of motor imagery events occurred in real-time using a classifier based on the analysis of electroencephalographic (EEG) activity patterns. The accuracy (proportion) of recognizing motor imagery for both the left and right hands was evaluated across five experimental sessions.
Results. It was demonstrated that learning followed a U-shaped trajectory: following an initial decline in recognition rates during the midpoint of the training sessions (dropping from baseline levels of 76% and 80% to 66% and 71% for the right and left hands, respectively), there was significant improvement by the fourth or fifth session, achieving peak values throughout the experiment (approximately 85% and 90%, respectively). This indicated the establishment of stable neural representations.
Conclusion. Acquisition of motor imagery skills through a brain-computer interface incorporating visual and vibrotactile feedback exhibits a U-shaped learning curve, culminating at its highest point on the fifth day of training.

Keywords: brain – computer interface, motor imagery, motor imagery skill, biofeedback

Cite as: Badarin AA, Antipov VM, Piljugin OV, Novikov MYu, Kiselev AR, Drapkina OM. Dynamics of motor imagery skill formation using a brain – computer interface with multimodal feedback. *Saratov Medical Journal* 2025; 6 (4): e0403. https://doi.org/10.15275/sarmj.2025.0403

Introduction

Currently, both cognitive and motor impairment resulting from central nervous system pathologies denote a significant challenge in healthcare, leading to decreased work capacity and reduced quality of life in patients [1, 2]. A promising direction for preventing and treating such disorders is the application of brain-computer interface technology (BCI), which adapts rehabilitation process by tailoring it specifically to an individual's unique needs and capabilities.

A key element in implementing such rehabilitation BCIs is the execution motor imagery. The letter engages neural networks associated with sensorimotor and cognitive functions without requiring actual physical movement. This approach contributes to the neuroplasticity of the brain and is particularly effective during the initial rehabilitation phase when performing actual movements be difficult or impossible for the patient [3–5].

In this context, biofeedback aims at developing self-regulation skills in patients [6, 7]. Thus, by interacting with the computer appliance, the patient learns to consciously reproduce the patterns of brain activity aimed at controlling the BCI. This is especially important for rehabilitation measures since the development of such skills requires understanding one's own mental state, along with the development of motor responses.

Divergence between objective indicators of motor activity and the subjective state may indicate insufficient conscious control over recovering functions. Therefore, an analysis of the relationships between the patient's objective and subjective state relevant for improving rehabilitation programs for their cognitive and motor disorders using BCI [3].

Previously, we developed a new technology in the form of a rehabilitative computer appliance prototype with BCI. This technology uses motor imagery as part of visual and vibrotactile biofeedback to address various cognitive and motor disorders [3, 8].

However, the formation of motor imagery skills in patients within the context of their engagement in interactive BCI-based rehabilitation remains insufficiently studied. This could be an important limiting factor of clinical effectiveness.

Objective: to assess the dynamic of motor imagery skill formation while using BCI with visual and vibrotactile biofeedback.

Material and Methods

The study was conducted in accordance with the principles of the Declaration of Helsinki and received approval from the Independent Ethics Committee of the Federal State Budgetary Institution «National Medical Research Center for Therapy and Preventive Medicine» of the Ministry of Health of the Russian Federation (extract from protocol No. 06-05/25 dated October 15, 2025). Informed consent was obtained from all study participants.

The pilot study included 10 healthy volunteers aged 29–34 years. All participants were right-handed.

A multi-day experiment was conducted to assess the dynamic of skills formation in motor imagery during regular training under conditions of multimodal biofeedback. The protocol used two feedback channels: visual and vibrotactile.

- Visual feedback was provided by an animation of a bending palm on the screen, activated when movement was successfully recognized.
- Vibrotactile feedback was delivered via a vibratory stimulator placed on the palm of the corresponding hand of the participant.

This combination of modalities facilitated more effective integration of sensory streams and enhanced the neural representation of imagined movement. Consequently, it supported the formation of stable motor images and maintained active participant engagement throughout each session.

The experiment lasted five days, with one rehabilitation session per day. Each session included tasks involving motor imagery of the left and right hands. This design allowed us to monitor:

- gradual adaptation to training conditions;
- stabilization of task execution strategies;
- changes in the quality of generated motor images over the entire observation period.

Electroencephalogram (EEG) recording was performed throughout each experimental session. Detecting moments of motor imagery was carried out in real time using a classifier based on analysis of EEG activity patterns, as described in our previous works [3].

Experimental procedure:

1. Prior to the experiment, oculomotor activity was calibrated and background EEG was recorded for 60 seconds.
2. A participant then adapted to detect motor imagery by mentally squeezing the palm of the corresponding hand. The experiment included tasks on imagining movements of both hands.
3. The main part of the experiment involved mental execution of movements. When successful recognition occurred, biofeedback (visual and/or vibrotactile) was provided.
4. The total duration of one session was approximately 30 minutes.

Data analysis:

While analyzing the experimental data, the accuracy of recognizing motor imagery for the left and right hands was evaluated across five experimental sessions. Success reflected the proportion of effectively performed imagination trials, where each trial consisted of a 10-second interval during which the subject had to form a stable motor image of the movement of the given hand. If the imagined action reached the required level of intensity and matched the target EEG pattern, the classification algorithm recorded successful recognition.

To assess the influence of the experimental session factor on the success rate of recognizing motor imagery, repeated measures analysis of variance (RM ANOVA) was applied separately for each hand. The effect size was estimated using partial eta-squared ($\eta p2$). The level of statistical significance was set at $p<0{,}05$. The data are presented as the mean value and its standard error.

Results

The *figure* shows the dynamics of recognition accuracy for motor imagery of the left and right hands over 5 experimental sessions. RM ANOVA revealed a statistically significant effect of the session factor on the recognition accuracy of motor imagery for both the right hand ($p=0{,}003$, $\eta p2=0{,}35$) and the left hand ($p<0{,}001$, $\eta p2=0{,}41$). The dynamics of recognition accuracy for motor imagery show a clear U-shaped learning trajectory for both hands.

In the 1st session, the recognition accuracy for motor imagery is at a fairly high level: approximately 80 % for the right hand and approximately 76 % for the left hand. By the second session, the recognition accuracy slightly decreases, and by the 3rd session it reaches its minimum values: approximately 71 % for the right hand and approximately 66 % for the left hand. From the fourth session onward, the recognition accuracy begins to gradually recover. However, the most pronounced rise is observed between the fourth and fifth sessions: the recognition accuracy for motor imagery of the right hand increases by more than 10 %, and for the left hand by nearly 20 %, reaching maximum values over the entire period of the experiment (approximately 85 % and 90 %, respectively).

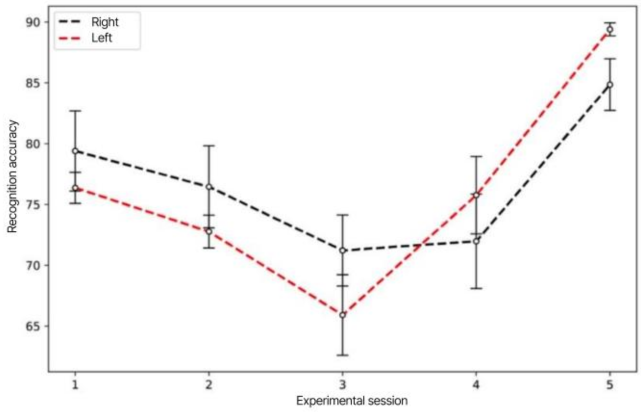

Figure. Dependence of recognition accuracy for motor imagery of the left and right hands over five-day experimental session

Discussion

The "sag" effect in the accuracy of recognizing motor imagery in the middle of the experiment is typical in training protocols and represents an adaptation phase, when the participant restructures their internal strategy in the formation of the motor image. At this stage, a person transitions from more superficial intuitive imagination to a more structured, specific motor image, which temporarily reduces the stability of the task execution. This assertion is consistent with research data showing that learning to control a brain-computer interface (BCI) is a skill that requires practice and adaptation, and the restructuring of neural patterns can affect signal stability [9, 10].

The increase in success from the fourth day of the experiment reflects the formation of stable, reproducible neural patterns corresponding to motor imagery and improved alignment between the motor image and the algorithm for its recognition. Long-term training with biofeedback does indeed contribute to the formation of such stable self-regulation skills [11, 12].

A noteworthy asymmetric effect between the hands is evident. Throughout the first four sessions, the success rate of imagining movements of the right hand remained consistently higher than that of the left hand. This outcome aligns with expectations given that all participants were right-handed; thus, motor representations associated with the right hand are likely to be more familiar and robustly established neurally. This observation is corroborated by prior research indicating that in right-handed individuals, motor representations related to the dominant (right) hand typically induce stronger and more lateralised activations of sensorimotor rhythms, potentially enhancing their detectability [13].

However, by the fifth session the situation changes — the accuracy for the left hand becomes higher than for the right. This may reflect a compensatory effect: the participant, noticing that imagining movements of the left hand is more difficult, begins to pay more attention and exert greater effort. This redistributed focus and increased control lead to a sharp rise in the recognition accuracy of motor imagery specifically for the left hand.

Thus, the obtained data demonstrate a typical trajectory of the learning process: an initial high level, followed by a decline during the strategy restructuring phase, and subsequent significant improvement in task performance. The results of the 5th session confirm that a multi-day training protocol effectively promotes the strengthening of motor imagery skills, stabilization of neural representations, and improved interaction between the user and the recognition system.

Conclusion

The development of motor imagery skills when utilizing a BCI equipped with visual and vibrotactile biofeedback demonstrates a characteristic U-shaped trajectory, with maximal improvements achieved by the fifth day of training. Our investigation confirmed the efficacy of employing a multi-day regimen—specifically, a five-day program—in conjunction with multimodal biofeedback to establish stable motor imagery skills. The observed learning pattern mirrors the inherent processes of neurocognitive adaptation and reorganization among participants. These insights have practical implications for optimizing rehabilitation programs leveraging BCIs, notably regarding determination of minimal necessary training durations and forecasting patient recovery trajectories.

Authors' contributions. The authors made equivalent contributions to the writing of the article.

Conflict of interest. The authors declare no conflict of interest.

Funding sources. The study was conducted within the framework of the research project "Development of a hardware-software complex for rehabilitation of patients with cognitive and motor impairments of various origins based on multimodal biofeedback," carried out at the National Medical Research Center for Therapy and Preventive Medicine of the Russian Ministry of Health in accordance with the state assignment of the Russian Ministry of Health No. 123020600127-4 (2023–2025).

Informed consent for publication. The patients signed a voluntary informed consent form for the publication of medical information.

Ethics compliance. The study protocol was approved by the local ethics committee (extract from protocol No. 06-05/25 dated October 15, 2025). The approval and procedure for conducting the protocol were obtained in accordance with the principles of the Declaration of Helsinki.

References

1. Feigin VL, Brainin M, Norrving B, et al. World Stroke Organization: Global Stroke Fact Sheet 2025. *Int J Stroke*. 2025; 20(2): 132-44. https://orcid.org/10.1177/17474930241308142
2. Mokienko OA, Suponeva NA, Aziatskaya GA. Stroke in adults: Central paresis of the upper limb. Clinical guidelines. Ed. by O.A. Mokienko, N.A. Suponeva. *Moscow: MEDpress-Inform* 2018; 108 p. (In Russ.)
3. Antipov VM, Smirnov NM, Badarin AA, et al. Using brain–computer interfaces for personalized neurorehabilitation: The role of subjective perception and neurophysiological indicators. *Medical doctor and information technology* 2025; (2): 84-97. (In Russ.)
4. Khorev V, Kurkin S, Badarin A, et al. Review on the use of brain computer interface rehabilitation methods for treating mental and neurological conditions. *J Integr Neurosci*. 2024; 23(7): 125. https://orcid.org/10.31083/j.jin2307125
5. Hramov AE, Maksimenko VA, Pisarchik AN. Physical principles of brain – computer interfaces and their applications for rehabilitation, robotics and control of human brain states. *Physics Reports* 2021; 918:1-133. https://orcid.org/10.1016/j.physrep.2021.03.002
6. Ulloa ER, Pineda JA. Recognition of point-light biological motion: Mu rhythms and mirror neuron activity. *Behav Brain Res*. 2007; 183(2): 188-94. https://orcid.org/10.1016/j.bbr.2007.06.007
7. Bauer R, Gharabaghi A. Estimating cognitive load during self-regulation of brain activity and neurofeedback with therapeutic brain – computer interfaces. *Front Behav Neurosci*. 2015; 9:21. https://orcid.org/10.3389/fnbeh.2015.00021
8. Antipov VM, Badarin AA, Kurkin SA, et al. Hardware-software complex for rehabilitation of patients with cognitive and motor disorders. *Medical Doctor and Information Technology* 2024; (4): 38-47. (In Russ.) https://doi.org/10.25881/18110193_2024_4_38
9. Allison BZ, Neuper C. Could anyone use a BCI In: Brain–computer interfaces. *Human-Computer Interaction Series. London: Springer* 2010; p. 35-54. https://orcid.org/10.1007/978-1-84996-272-8_3

10. Finnis R, Mehmood A, Holle H, Iqbal J. Exploring imagined movement for brain – computer interface control: An fNIRS and EEG Review. *Brain Sci.* 2025; 15(9): 1013. https://orcid.org/10.3390/brainsci15091013
11. Zich C, Vos MD, Kranczioch C, Debener S. Wireless EEG with individualized channel layout enables efficient motor imagery training. *Clin Neurophysiol.* 2015; 126(4): 698-710. https://orcid.org/10.1016/j.clinph.2014.07.007
12. Naros G, Naros I, Grimm F, et al. Reinforcement learning of self-regulated sensorimotor β-oscillations improves motor performance. *NeuroImage* 2016; 134: 142-52. https://orcid.org/10.1016/j.neuroimage.2016.03.016
13. Zapała D, Iwanowicz P, Francuz P, Augustynowicz P. Handedness effects on motor imagery during kinesthetic and visual-motor conditions. *Sci Rep.* 2021; 11(1): 13112. https://orcid.org/10.1038/s41598-021-92467-7

Authors:
Artem A. Badarin – PhD, Senior Researcher of the Coordinating Center for Fundamental Research, https://orcid.org/0000-0002-3212-5890;
Vladimir M. Antipov – PhD, Expert of the Coordinating Center for Fundamental Research, https://orcid.org/0009-0003-9612-0305;
Oleg V.Piljugin – Research Assistant of the Baltic Center for Neurotechnologies and Artificial Intelligence, https://orcid.org/0000-0001-8998-0217;
Mikhail Yu. Novikov – Junior Researcher of the Coordinating Center for Fundamental Research, https://orcid.org/0000-0002-0876-7201;
Anton R. Kiselev – DSc, Professor, Head of the Coordinating Center for Fundamental Research, https://orcid.org/0000-0003-3967-3950;
Oksana M. Drapkina – DSc, Professor, Academician of the Russian Academy of Sciences,Director, https://orcid.org/0000-0002-4453-8430.