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PHYSIOLOGY OF HIGHER NERVOUS (MENTAL) ACTIVITY IN HUMANS

A Motor Imagery-Based Brain–Computer Interface with Vibrotactile Stimuli

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Brain–computer interfaces (BCI) based on motor imagery allow people to use mental motor images recognized from the electroencephalogram (EEG) as control commands. With the aim of providing the most effective channel for interactions, interfaces of this type are under active development and modification, though all currently require use of the visual modality in the control loop. We have proposed an interaction scheme using such BCI employing the vibrotactile channel – without use of visual control elements. The interface described here was tested in 11 healthy subjects who were presented with the task of learning motor imagery and using it in the BCI control loop, guided by stimuli delivered in the tactile modality – using vibration stimulators attached to the body. This paradigm provides for assessment of the effectiveness of motor imagery training with the eyes closed. During the study, which lasted seven experimental days, all subjects successfully acquired the motor imagery skill. Thus, users were found to be able to learn to operate in the BCI control loop without using the visual channel, when stimuli to carry out commands and feedback are delivered via the vibrational modality. The characteristics of EEG activity, corticospinal excitability, session-by-session dynamics, and the accuracy of BCI use in this approach were at least no different from those in the classical scheme with visual delivery of stimuli and feedback, and for some users the new mode had advantages in terms of a number of measures. The BCI paradigm proposed here opens up the potential for use by people with poor vision and widens the range of practical applications of BCI.

Keywords: brain–computer interface (BCI), EEG, motor imagery, μ rhythm, corticospinal excitability, vibrotactile stimulation, desynchronization, TMS, closed eyes, ideomotor training.

Introduction. Brain–computer interface (BCI) technology allows people to learn to produce transient changes in brain activity which are read by recording the electroencephalogram (EEG) and transformed into commands for external executive systems [Wolpaw et al., 2002; Kaplan et al., 2013]. An effective method for voluntary triggering of EEG changes is provided by focusing attention on an external stimulus or mental image of a movement. Furthermore, it has long been known that assimilation of new motor acts in sportsmen is promoted by repeated performance of the corresponding movements in the imagination – ideomotor training [Schuster et al., 2011]. It is therefore no surprise that the use of brain–computer interface technology based on motor imagery relating to the subject's own body is popular for training and for restoration of impaired motor functions, for example in patients with neurological trauma and after stroke [Mulder et al., 2007; Simmons et al., 2008; Kaplan, 2016].

Patients with pareses and even people with limb amputations have been found to be able to imagine movements in both the visual and kinesthetic modalities and to be only slightly less good at this skill than healthy people [Malouin et

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al., 2009]. Despite the fact that a number of laboratories and clinics have made attempts to develop poststroke rehabilitation programs using neurological training devices based on brain–computer interfaces, only some of these have yielded positive clinical effects [Page et al., 2007; Frolov et al., 2013].

Motor imagery is known to be associated with well-developed EEG desynchronization of the sensorimotor μ rhythm, which also underlies the recognition of the corresponding mental act by the BCI [Friedrich et al., 2013; Pfurtscheller and Neuper, 1997]. It has also been shown that repeated training to mental motor imagery with feedback in the BCI loop leads to formation of the corresponding skill with enhanced EEG desynchronization and consequent improvement in the classification of EEG patterns [Mokienko et al., 2013; Toppi et al., 2014]. However, BCI methods based on motor imagery are quite complex to assimilate, especially by poststroke patients, and require improvement in training protocols and increased user involvement in the task in order to form a stable skill [Simmons et al., 2008]. Thus, it is important to develop specialized training regimes for motor imagery oriented, on the one hand, to maximizing the effectiveness of subsequent training with BCI and, on the other, to the potential for using neurotrainers in domestic conditions without the need for medical staff.

Many investigations have drawn attention to the need to provide suitable feedback to subjects during training to motor imagery and training in the BCI loop [Ono et al., 2013; Vuckovic and Osuagwu, 2013]. The presence of this feedback increases the accuracy of command classification in the brain–computer interface [Gonzalez-Franco et al., 2011], which appears to be related to formation of the motor imagery skill. In addition, feedback helps to increase the subject's motivation, his or her involvement in the task, and makes the training process interactive. The most widely used and best studied type of feedback is visual, which requires the subject to focus attention and gaze on the BCI control system (for example, changes in a marker on a screen) [López-Larraz et al., 2011]. Realistic tasks oriented to a concrete aim have been shown to work best (for example, the subject is given the task of imagining not simply clenching the fist, but is shown a ball on the screen which has to be thrown into a basket mentally) [Mulder, 2007; Vuckovic and Osuagwu, 2013]. As in the real motor act, eye and hand movement must be clearly correlated with each other and the same eye movements are needed in the mental imagery. Experiments with motor imagery of the hands with the gaze fixed [Heremans et al., 2011] showed that high learning accuracy and effectiveness can only be achieved in conditions of free eye movements. Correlations between motor imagery and eye movements are so strong that Poiroux et al. [2015] even suggested monitoring subjects' involvement and understanding of the task in terms of oculographic characteristics.

However, in real practice, it is not always possible to provide additional visual feedback, as the visual channel may be occupied processing the information required for the ongoing activity. For example, in the situation of controlling a wheelchair using a BCI, the patient must continuously follow displacements in space and possible obstructions in the path. This impels investigators to consider variants on the formation of feedback in other sensory modalities, for example, the tactile. The first brain–computer interface with eight vibrotactile stimulators applied to the skin of the shoulder girdle around the subject's body was presented by Cincotti et al. [2007a]. The authors noted that tactile information is recognized well by subjects, was comfortable for prolonged training sessions lasting up to an hour, and provided accurate control comparable with that obtained with the classical paradigm using visual feedback. A wider-ranging study was reported by the same group [Cincotti et al., 2007b], involving 33 subjects (including patients with paraplegia) and vibrotactile feedback was found to have advantages over visual feedback in complex visual tasks (closer to real-life situations). The authors noted that training to motor imagery was equally successful using the visual and vibrotactile means of delivering feedback, though vibration responses were perceived subjectively as more natural. Thus, selection of feedback modality must take account of subjects' preferences, the availability of the visual channel, and the design of the device to be controlled by the BCI.

However, the use of vibrotactile stimuli in the motor imagery-based brain–computer interface loop can in and of itself lead to the occurrence of EEG reactions of the desynchronization type, which can complicate classification of EEG patterns in the BCI [McCormick et al., 2007]. Yao et al. [2013] tested how vibrotactile stimulation delivered to the wrist was combined with motor imagery in EEG reactions. These studies showed that classification of motor imagery patterns of the right and left hands was accurate in conditions of selective attention by the subjects to vibration stimulation of the target hand during motor imagery. The subjects noted that this stimulation did not distract them from the main task. Furthermore, tactile stimulation was particularly effective for subjects with "BCI incompetence," thus widening the potential applications and availability of this brain–computer interface for larger numbers of patients [Yao et al., 2013].

Similar results evidencing successful use of vibrotactile feedback in BCI construction projects based on motor imagery were presented by Leeb et al. [2013]. These authors did not find any statistically significant differences between systems using visual and vibrational feedback. Chatterjee et al. [2007] emphasized that vibrotactile feedback can be convenient in modeling control of a neuroprosthesis using a BCI, providing the patient with adequate sensory information. Apart from vibration sensors, feedback for the BCI could also consist of functional electric stimulation of muscles, which, as compared with the use of visual feedback, improves both learning of motor imagery and the accuracy of control in the brain–computer interface loop [Bhattacharyya et al., 2016]. These authors also noted that the use of the proprioceptive channel aids subjects' concentration on the task and their ability to maintain a high level of motivation during training.

However, in these studies only feedback for the BCI was tactile; delivery of the stimulus designating the start of the command still used the visual sensory channel. This construction of neurocomputer interfaces makes them unsuitable for people with various visual impairments: blindness, as well as difficulties with eye movement and focusing [Rutkowski and Mori, 2015]. At the same time, even completely blind patients have been found to be capable of motor imagery. Malouin et al. [2009] found that both visual and kinesthetic motor imagery in a group of subjects with late-onset blindness was greater than that in a control group of healthy subjects of the same age. Kober et al. [2004] found that EEG desynchronization patterns in the central areas of the cortex in kinesthetic motor imagery of the hands showed no differences between groups of blind and seeing subjects.

An extensive systematic review [Schuster et al., 2011] addressed 133 experimental studies of training based on motor imagery in education, medicine, music, psychology, and sport, and indicated that motor imagery in most studies was performed with the eyes closed. This practice led to more successful training results. This can evidently be explained by the fact that decreases in incoming sensory information lead people to form a brighter kinesthetic image, which correlates with the extent of the physiological effect [Vasilyev et al., 2017]. At the same time, the typical practice of working in the BCI loop involves having the eyes open. We did not find any published data on brain–computer interfaces based on motor imagery in which the subjects were asked to work with the eyes closed.

Thus, the aim of the present work was to study the formation of the motor imagery skill in users of a brain–computer interface with vibrotactile delivery of stimuli and feedback in the same modality, as well as to evaluate the electrophysiological characteristics of the formation of the motor imagery skill with the eyes closed.

Methods. ***Subjects.*** A total of 11 volunteers (10 women, one man) aged 19–27 (mean 24.4 ± 0.7) years took part in the study. None of the subjects had previous experience of working with neurocomputer interfaces. None had been diagnosed with neurological or mental diseases. All were right-handed on the Edinburgh manual asymmetry questionnaire [Oldfield, 1971]: coefficients of asymmetry averaged +73 ± 8. Subjects were familiarized with general information on the experiment and signed voluntary informed consent to take part in the study. The study protocol was approved by the Ethics Committee of the Faculty of Biology, Lomonosov Moscow State University.

EEG recording. The electroencephalogram (EEG) was recorded during studies using a BrainVision actiCHamp encephalograph (Brain Products GmbH, Germany) using 64 Cl/Ag active electrodes positioned according to the 10–10 system. Reference electrodes were TP9 + TP10 and the ground electrode was Afz. Electrodes were mounted using conducting gel to give contact resistance of no more than 20 kΩ. Signal sampling frequency was 500 Hz, and traces were made using a filter passing frequencies of 0.1–60 Hz and a 50-Hz electrical network rejection filter. Data were recorded in BCI2000 software [Schalk et al., 2004].

Recording of EMG and event-related motor responses. The electromyogram (EMG) was recorded using pairs of superficial Ag/AgCl electrodes (ED6, EasyCap GmbH, Germany) from the flexor digitorum superficialis muscle of the right hand. The skin beneath the electrodes was washed with alcohol wipes and abrasive paper to decrease contact resistance; resistance was no greater than 5 kΩ. The signal was recorded using an NVX52 amplifier (Medical Computer Systems, Russia). The signal sampling frequency was 10 kHz and recordings used a filter passing 5–350 Hz with a fourth-order digital Butterworth filter.

Single-pulse transcranial magnetic stimulation (TMS) was performed using a Neuro-MS/D magnetic stimulator (Neurosoft, Russia) with a figure-eight coil. The "hot point" for the flexor digitorum superficialis muscle of the right hand was found and the stimulation parameters were established such that motor event-related potentials (MEP) in the resting state were 0.4–0.8 mV (~110–115% of the motor response threshold). EMG recording and processing were run on the Resonance platform (developed by Yu O. Nuzhdin).

Study protocol. Each subject took part in seven experimental sessions each of duration 90–150 min. During experiments, subjects sat in a comfortable chair with armrests. Throughout the session, the subject was trained to imagine the same movement – sequentially tapping the support with the fingers from an initially relaxed hand position – using the right and left hands separately. Our previous studies [Vasilyev et al., 2016] showed that this movement was not only subjectively easier to carry out by users, but was also classified better. The reference state was the cognitive task of carrying out mental arithmetic. The cognitive task provided better distraction from motor imagery and created an easily reproducible baseline EEG pattern without motor activity.

Experimental sessions consisted of 10–22 recordings of duration 2–4 min. In each trace the subject was asked to perform two types of command in sequence: to imagine the movement of one hand and carry out mental arithmetic or to sequentially imagine the movement of each hand. This recording regime provided constant focusing of the user on the task and prevented drowsiness (which could be expected given the lack of visual information input with the eyes closed). Each trace consisted of a sequence of 12 commands. The duration of command presentation was 10–13 sec.

During traces, the signal to start performing motor imagery of the right or left hand was given using the vibromotors (3 V, 12000 rpm, motor diameter 10 mm, surrounded by a metal body of diameter 24 mm) positioned on the wrist of the corresponding hand, while the signal to carry out the cognitive task was delivered using an analogous vibromotor positioned on the back of the subject's neck (beneath the collar). The vibromotors were attached to the skin of the hand using flexible Velcro tapes of the appropriate size. The beginning of a command was marked by giving a triple vibrational signal of duration 1000 msec (three signals each of 200 msec with pauses of 20 msec).

The aim of the first two sessions was to familiarize the subject with the process of motor imagery with the eyes closed. The subject initially performed the movement for real, at full amplitude, concentrating on the kinesthetic sensations; the amplitude of the muscle contractions was then decreased all the way to complete disappearance (identified by electromyograms). During performance of any kind of movement, the subject told him- or herself which finger to use at each moment of the motor image with the aim of increasing concentration (delivery of the mental command). Each motor imagery trial consisted of sequential images of finger movements in the order specified to the subject arbitrarily.

In the third and fourth sessions, the BCI loop included vibrational feedback delivered via the same vibromotors as the commands. The signal for confirming correct classification of state consisted of a single prolonged (600 msec) vibration. Confirmation was given at the end of the command only when it was correctly recognized (above the specified threshold level).

In the fifth and sixth sessions, formation of a stable motor imagery skill with the eyes closed was monitored by making traces with analogous sequences of commands with the eyes open. Signals identifying the beginnings of commands were still presented using the vibromotors rather than visually. During traces with the eyes open, the subject had to avoid directing the gaze to the hands (to avoid provoking visual imagery in place of kinesthetic).

In the seventh session, the dynamics of corticospinal excitability were measured by TMS during motor imagery. During each trace with TMS, the subject carried out two types of command – motor imagery of one hand (the experimental condition) and the cognitive mental arithmetic task (control condition). Commands for subjects were delivered using vibromotors with the same vibration patterns as in previous sessions. Commands were given in sequences of three (AAABBBAAABBB... to a total of 30 commands in each trace), and during each command a TMS discharge was delivered at a random time point in the period 2–5 sec from the beginning of vibration. A total of 150 motor responses were recorded from each subject during the seventh session: 15 during motor imagery of the left hand with the eyes closed, 30 during motor imagery of the right hand with the eyes closed, 45 during performance of the cognitive task with the eyes closed, 30 during motor imagery of the right hand with the eyes open, and 30 during performance of the cognitive task with the eyes open.

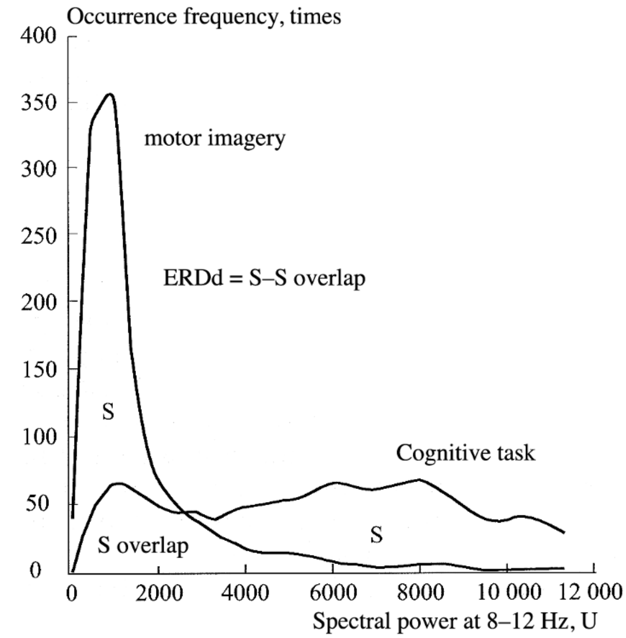


Fig. 1. Example Showing calculation OF ERDd for a trace from one subject. The spectral power distribution in the band 8–12 Hz in the spatially filtered channel (CSP) is shown for two states: motor imagery and cognitive task (reference state). Areas under the distribution curves (S) are taken as 100%. ERDd takes values from 0 to 100.

During sessions with TMS, the monitor in front of the subject and experimenter displayed real-time EMG activity. The EMG was presented as vertical bars with mean square values (computed online) of signal amplitudes (in a sliding window of length 300 msec with a 100-msec step). At the beginning of the session subjects had to find the hand position producing the minimal baseline EMG amplitude; throughout all recordings the experimenter monitored maintenance of the ongoing level of muscle activity detected.

EEG analysis. Data were analyzed using the Resonance platform (developed by Yu. O. Nuzhdin). Analysis of EEG traces identified epochs corresponding to subjects' attempts at states; the time segment of 1.5 sec from stimulus delivery (to the beginning of the trial) was excluded from analysis. The method used for analysis of individual EEG characteristics is described below.

Classification and analysis of EEG patterns. Characteristics of EEG patterns significant for classification were identified by filtering the trace in the band 6–40 Hz and then computing transformation matrixes for individual spatial CSP (common spatial pattern) filters [Koles, 1991], which has been used successfully for recognizing motor imagery patterns [Ramoser et al., 2000]. After transformation of the spatial domain of the signal (by multiplication by the transformation matrix), each channel was identified separately in the spectral domain. For each of the two states being compared, the probability density of each spectral component in the range 7–30 Hz was regenerated (coefficients of the

Fourier decomposition window extracted using a rectangular window function of width 1 sec with 0.1-sec displacements). The resulting densities for each component were compared for the two patterns of the states being classified, with subtraction of the overlap region (see Fig. 1 for graphical explanation). The value corresponding to 100% minus the overlap area (percentage of the area under the probability density curve) was termed ERDd and was used in studies for quantitative assessment of the extent of the EEG reaction arising on motor imagery.

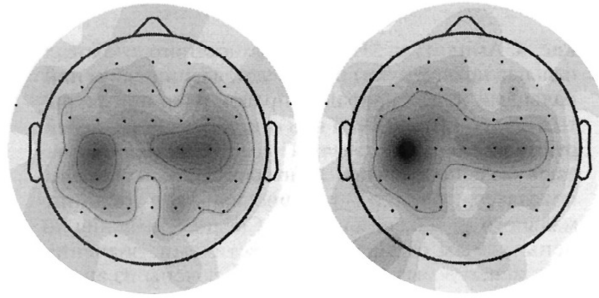
The three spatial-spectral metrics with the greatest ERDd values were used for training a Bayesian classifier. The sampling frequency of the classifier was 10 Hz with a sliding average of five sequential values. The a posteriori probabilities of each of the two classes (A and B) for the vector of metrics ($\tilde{x}$) computed by the classifier was converted to binary form using a threshold established individually for each subject (for example, $P(A|\tilde{x}) > 0.65 \Rightarrow$ "Class A," $P(A|\tilde{x}) > 0.60 \Rightarrow$ "Class B," otherwise "Ø" – no class).

Assessment of classification accuracy. Cross-validation using a 5 × 2 scheme was used for consistent assessment of classification accuracy achieved by subjects working with the BCI. Ongoing traces were sequentially identified containing trials of the two states being classified – motor imagery with determination of the stimulus delivery mode and the cognitive task (mental arithmetic) state. The resulting blocks contained 3–4 traces including 18–24 trials for each state. Cross-validation was performed by randomly dividing the block into two equal parts containing identical numbers of trials of one class. The classifier was then trained using one part, followed by testing with the other, followed by training and testing the other way round. This operation, including "splitting" of the block and the following two "training–testing" stages, was performed five times. A posteriori probabilities obtained by testing the classifier were averaged over time in the framework of each trial and were transformed into binary solutions – trials were regarded as successfully classified if the probability of a correct classification was greater than 0.5. Classification accuracy was taken as the ratio of the number of trials classified correctly to the total number of trials. The time dynamics of classification of a posteriori probabilities were averaged for trials (point by point).

Topographic mapping of EEG patterns. The spatial (topographic) locations of features used for classification were evaluated by projecting coefficients of the computed spatial filter (the CSP) onto the positions of the initial leads. The vectors of the spatial filter corresponding to the five best features were multiplied by their ERDd values, absolute values were summed, and the results were applied to a two-dimensional model of the EEG recordings.

The resulting topographic maps provide assessments of the quantitative contributions of individual EEG leads to classification features.

Analysis of motor event-related potentials. Changes in corticospinal excitability in the test conditions were assessed in terms of changes in the amplitudes of motor event-related potentials. MEP amplitudes were computed by the peak-to-peak method (from the positive peak to the negative peak of the potential). Changes in amplitude were evaluated in comparison to the reference state (mental arithmetic) as the ratio of mean values of potentials obtained during a single trace (30 stimuli). Potentials with preceding TMS pulses of muscle activity (10–20%) were excluded from the analysis.



Left hand Right hand

Fig. 2. Topographic maps of EEG patterns averaged for all subjects (N = 11) on motor imagery of the fingers of the right and left hands with the eyes closed. Weighted channel coefficients are shown: dark areas show greater values and light areas show smaller values.

Statistical analysis. Study results were processed statistically in Statistica 10 (StatSoft). The significance of subjects' individual results (increases in MEP, comparison of classification accuracy in two conditions in individual subjects) was assessed using the Mann–Whitney test. The Friedman test was used for multiple linked sets (session-by-session analysis of ERDd, mean excitability in three presentation conditions). The Wilcoxon test for paired comparisons was used when the significance threshold of the Friedman test was exceeded and for testing pairs of linked sets (group effects by classification accuracy). Correlation of parameters was assessed using the Spearman coefficient. The threshold of statistical significance for all tests was $p < < 0.05$. For convenience, data are presented using Microsoft Office Excel 2010 and MathWorks MATLAB2016b.

Psychological testing. In the middle of each session, subjects were given the "Scale of States" questionnaire [Leonova and Kuznetsova, 2015]. This method was used to assess the level of subjective comfort of the functional state experienced by the person during the experimental session.

Results. ***Characteristics of EEG patterns in motor imagery.*** Results were analyzed using a mean of 90 separate EEG traces from each of 11 subjects: motor imagery for the right hand in 38 of these was classified against the cognitive task, in 34, motor imagery of the left hand was classified against the cognitive task, and in 18 motor imagery of one hand was classified against that of the other.

Spearman correlation analysis showed that ERDd and BCI classification effectiveness values were tightly related

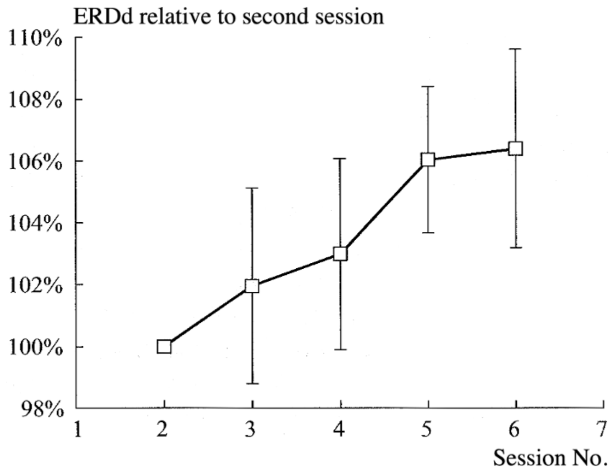


Fig. 3. Relationship between ERDd for motor imagery of the fingers and session number. Values for all sequential sessions for each subject are relative to the mean values for the second session. Error bars show standard errors of the mean.

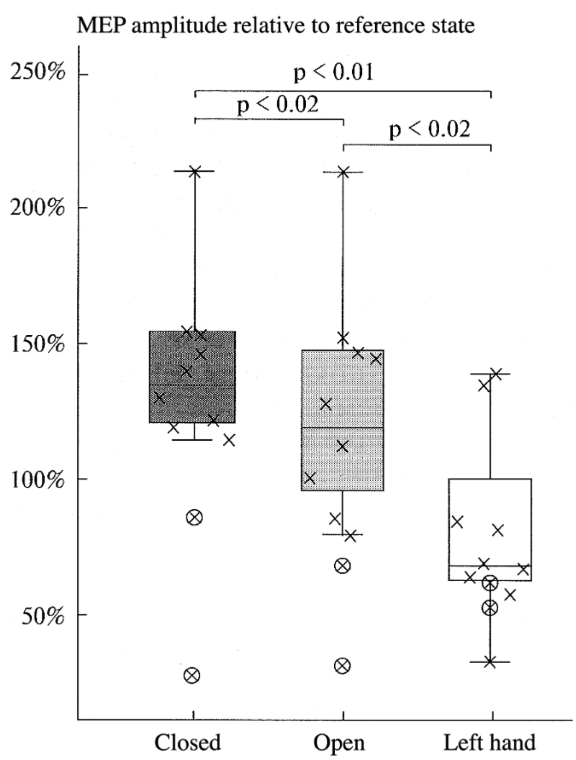


Fig. 4. Amplitude of MEP (flexor digitorum superficialis, right hand) on motor imagery of the fingers (left to right): right hand with eyes closed, right hand with eyes open, left hand with eyes closed. Rectangles show medians ± interquartile ranges; bars show ranges of values (minimal to maximal). Mean values for subjects are shown by crosses; values for two subjects circled) were excluded from analysis. Statistical significance of group differences is shown for the Wilcoxon signed-rank test (N = 9).

to each other (correlation coefficient 0.91). This linkage between these parameters allowed ERDd to be used for further

TABLE 1. Classification Accuracy (vs. cognitive task) in BCI and ERDd for Motor Imagery of Fingers with the Eyes Open and Closed for All Subjects. Figures in Bold Show Classification Accuracies Statistically Significantly Different for the Conditions Open Eyes and Closed Eyes (Mann–Whitney test, $p < 0.05$) for That Subject. Mean Values ± Standard Errors Are Shown for ERDd

	BCI accuracy (sessions 4–6)		ERDd (all sessions)	
	closed	open	closed	open
AB	**0.81**	**0.54**	56.6±1.15	54.2±1.78
AP	0.97	0.99	83.8±0.85	87.9±1.09
EV	**0.61**	**0.72**	54.1±0.99	65.0±3.66
FS	0.99	0.97	84.5±0.83	88.1±1.18
KM	**0.60**	**0.71**	49.8±1.12	61.2±3.49
LM	0.97	0.94	78.7±1.06	81.3±1.28
MA	**0.77**	**0.65**	51.0±0.98	52.8±2.18
NS	0.97	0.98	74.0±0.97	78.3±2.63
NV	0.95	0.95	70.2±1.13	72.9±1.82
PF	0.94	0.99	78.4±1.25	83.6±2.34
SM	0.94	0.99	70.1±1.22	78.1±1.64
Mean	0.87±0.04	0.86±0.05	68.6±0.60	74.2±1.11

analysis of the results for assessment of classification accuracy by the BCI.

Comparison of ERDd in traces with motor imagery for the right or left hands did not identify any significant differences between them (Mann–Whitney test, U = 74650 $p <$ < 0.63). For further analysis, all measures were therefore computed for trials with motor imagery for either hand.

The topographic distribution of ERDd in motor imagery of the left hand as compared with the cognitive task with the eyes closed and with vibrotactile delivery of stimuli revealed characteristic patterns of desynchronization in the central leads (Fig. 2). Activation was bihemispheric, though for motor imagery of the fingers of the right hand activation was stronger in the dominant (left) hemisphere. Similar topographic maps were also seen for motor imagery of finger tapping in the classical paradigm (with the eyes open and visual stimuli) [Vasilyev et al., 2016].

Learning effect. This is the first study reporting attempts to develop a stable motor imagery skill in users in condition of vibrational stimulus delivery with the eyes closed.

A learning effect was seen, in that the expression of patterns (in terms of ERDd) associated with motor imagery of the hand increased with the number of sessions. Mean ERDd for motor imagery of the hand on the background of the cognitive task by study days was assessed relative to the value on day 2, and these results are shown in Fig. 3. The first and last days of the study were excluded from the analysis: on day 1, subjects performed real movements in most traces as training to the method; an insufficient number of EEG traces was made on the last day, because of TMS test-

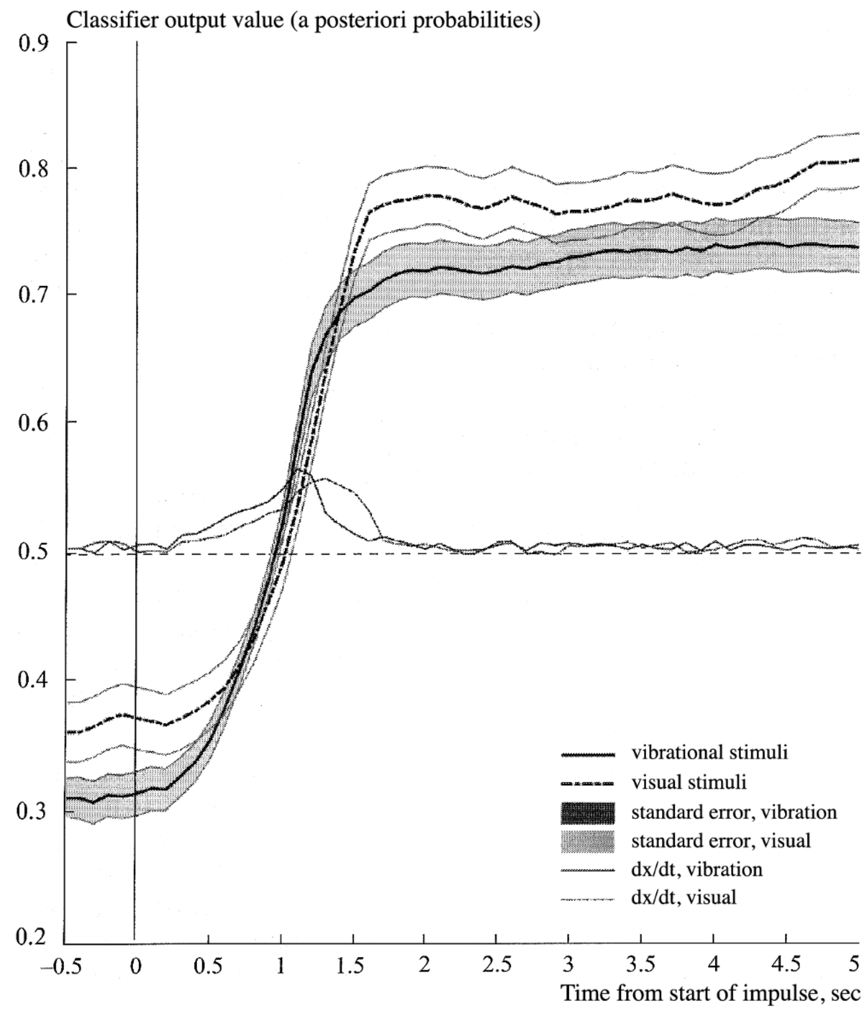


Fig. 5. Dynamics of classifier output for recognition of motor imagery trials specified using visual (13 subjects, 20 trials/subject) and vibrotactile (11 subjects, 24 trials/subjects) stimuli. Curves show mean values, along with standard errors and first derivatives. The threshold for correct recognition is shown by the horizontal dotted line ($p > 0.5$).

ing. Due to high between-session variation in some subjects, no statistically significant relationships between values and session number were seen at the group level. However, an increase was characteristic of most subjects, indicating that there was a learning effect.

Effectiveness of BCI classification. As stimuli at the beginnings of commands were delivered by vibration, not acting on the subject's visual attention, the study provided the opportunity to compare whether changes in EEG patterns during motor imagery of the hand occurred on blockade of the visual channel (with the eyes closed). On motor imagery of either hand on the background of the cognitive task, mean classification accuracy was 0.86 (with a between-individual range of 0.54 to 0.99) (see Table 1). At the group level, there were no statistically significant differences between regimes with the eyes closed and open. However, analysis of individual values for four subjects showed that one regime gave statistically significantly better results. This comparison was run using the Mann–Whitney test used for the output values of the classifier (a posteriori probabilities) for separate trials in a given subject.

All subjects taking part in the study demonstrated sufficient online classification accuracy for two states (motor imagery of the hand or the cognitive task). In traces in which motor imagery tasks with the right and left hands alternated (without trials using the cognitive task), classification effectiveness was lower (mean 0.66, range 0.51–0.99). This result is consistent with data obtained in our previous study using the classical BCI paradigm (open eyes, visual stimulation on a monitor) [Vasilyev et al., 2016] and with data from other investigators [Ahn and Jun, 2015].

Effects of motor imagery on corticospinal excitability. Transcranial magnetic stimulation studies showed that nine of 11 subjects displayed significant (Mann–Whitney test, $p < 0.05$) increases in the motor response amplitude of the flexor digitorum superficialis of the right hand on motor imagery of this same hand. Conversely, excitability in any motor imagery regime decreased in two subjects, so for further analysis these were excluded from the cohort. On average, the amplitude of the motor response with the eyes closed was 149 ± 13% compared with the reference state; with the eyes open it was 125 ± 14% of this state (Fig. 4).

At the same time, motor imagery of the contralateral (left) hand gave a motor response in the right hand which was lower than that on stimulation on the background of the cognitive task (on average, 87 ± 11% of the reference state). Comparison of three conditions (motor imagery of the right hand with the eyes open; motor imagery of the right hand with the eyes closed; motor imagery of the left hand with the eyes closed) revealed significant differences (Friedman test [χ^2 (N = 9, df = 2) = 10.89, $p = 0.00432$]), and subsequent pairwise comparisons using the Wilcoxon test demonstrated statistically significant differences in all pairs ($p < 0.02$).

Thus, these studies demonstrate increased corticospinal excitability on motor imagery, which is consistent with our previous results using the classical BCI paradigm [Vasilyev et al., 2017]. It is important to note that with the eyes closed, MEP amplitude was statistically significantly greater than on motor imagery with the eyes open.

Comparison of classification speed for two BCI paradigms. In the studies reported here, the signal for the start of motor imagery with the fingers of the right or left hand were provided by the tactile input to the same hand. The stimulus-induced afferent reaction may therefore be the cause of the unwanted activation of the sensorimotor area of the cortex, thus affecting the classification accuracy of motor imagery-associated patterns. To assess this influence we compared the time dynamics of the classifier output values (a posteriori probabilities) after delivery of the stimulus for motor imagery in different BCI paradigms: with vibrational and with visual stimulus delivery (data from [Vasilyev et al., 2017]). The plot in Fig. 5 shows that there is no difference in classification speeds – the time taken for the classifier to reach a plateau was 1.7–2 sec after stimulus delivery both on visual coding and via tactile actions. Thus, in this stimulus delivery regime, it appears that on solution of the classification task there was no interference between the patterns of the target tasks (motor imagery and the cognitive task) and responses to vibrotactile stimuli.

Discussion. ***Characteristics of EEG patterns during motor imagery.*** Studies have shown that characteristic patterns of desynchronization of the μ rhythm can be distinguished in the sensorimotor (central) leads during kinesthetic motor imagery of the hands [Pfurtscheller and Neuper, 1997]. Psychological studies of motor imagery have mainly been performed in subjects with their eyes closed [Schuster et al., 2011], while in studies using BCI based on motor imagery, people generally perform tasks with the eyes open [Cincotti et al., 2007b], as it is easier to construct a suitable system for encoding commands and feedback in the visual field. Our task was to study whether or not it is possible to create an operative BCI paradigm with the eyes closed and vibrational delivery of stimuli.

This study showed that typical EEG patterns in motor imagery [Vasilyev et al., 2016] also persist in the new BCI paradigm: motor imagery of the fingers induced bilateral desynchronization of sensorimotor rhythms (Fig. 2). Vibration on the wrists did not lead to any additional changes in cortical activity, as might be expected considering somatosensory event-related potentials [Yao et al., 2014].

Thus, we can conclude that using vibrational delivery of stimuli to the wrists both with the eyes closed and with the eyes open produces EEG reactions typical of motor imagery, which is consistent with previous data from experiments with visual encoding of commands.

Learning effect. We showed that ERDd for motor imagery on the background of a cognitive task increases with increases in session number (Fig. 3), pointing to the development of a learning effect. Previous studies of the classical BCI paradigm (with visual presentation of commands) demonstrated analogous results [Angulo-Sherman and Gutiérrez, 2015; Toppi et al., 2014]. The learning effect is important both for the practical application of BCI devices and in neurorehabilitation procedures [Mokienko et al., 2013]. Our results show that vibrational delivery of commands and vibrational feedback are successfully perceived by users and can motivate subjects to continue BCI training.

BCI classification effectiveness. The present studies showed that use of vibrotactile stimulus delivery achieved identical levels of command classification accuracy by BCI regardless of the presence of a visual information stream (which changes on opening and closing the eyes). This is consistent with previous studies showing that people can successfully perceive vibrotactile information as a signal for conscious changes in cortical activity [Cincotti et al., 2007a; Leeb et al., 2013; Pichiorri et al., 2011]. Subjects successfully recognized vibrational stimuli and could respond by changing their mental state without long delays.

For most subjects, classification of states was successful regardless of the working regime (eyes closed or open), though it will be interesting consider the results of four subjects with the lowest BCI classification accuracy in more detail (MA, AB, KM, and EV). We performed additional statistical analysis, comparing classification success for motor imagery of the hand on the background of the cognitive task with the eyes open and closed for these subjects. This showed that EEG pattern recognition improved significantly in subjects MA and AB in the regime working with the eyes open (Mann–Whitney test, $p < 0.00002$). At the same time, the opposite result was typical of KM and EV: classification was more accurate with the eyes closed (Mann–Whitney test, $p < 0.00003$).

Brain–computer interface developers are of the view that individual tuning of parameters and operating regimes are of fundamental importance for creating working BCI devices [Vuckovic and Osuagwu, 2013; Yao et al., 2013]. In this study, we showed that the use of vibrotactile feedback in BCI devices allows an operating regime to be selected taking account of subjects' individual characteristics. For those users working better in the BCI loop with the eyes closed, use of nonvisual commend encoding is needed, and this need is well filled by vibrational stimulation. Thus, the boundaries of the application of this technology are expanded to include those people who were previously regarded as "BCI incompetent."

Effects of motor imagery on corticospinal excitability. Desynchronization of the μ rhythm is known to correlate positively with increases in corticospinal conductivity (measured in terms of the amplitude of the myographic response to transcranial magnetic stimulation of the motor cortex) [Takemi et al., 2013]. Our study showed that that users successfully learned to imagine hand movements in the new BCI paradigm: cortical excitability increased significantly on imagination of flexion of the fingers of the right hand as compared with the control state, which was apparent as an increase in the amplitude of the motor event-related response of the flexor digitorum superficialis of the corresponding hand, while motor imagery of the contralateral (left) hand did not induce any such increase in the amplitude of the motor response.

While assessment of increases in corticospinal excitability on motor imagery in most literature sources is performed with the eyes open, our study provided the opportunity to compare this measure with users' eyes closed. Thus, our subjects showed that increases in excitability on motor imagery with the eyes closed were greater than those obtained with the eyes open.

One study [Bashir et al., 2017] using an analogous protocol to test corticospinal excitability (TMS, power at 120% of the motor threshold) showed that in the resting state, motor event-related potentials with the eyes open were greater than those with the eyes closed. However, studies reported by Mercier et al. [2008] addressed the increase in MEP on motor imagery with the eyes closed and open in healthy subjects and found a tendency to a greater increase in corticospinal excitability when motor imagery was performed with the eyes closed. Our result is consistent with the observations demonstrated in this study, though in our larger cohort (N = 9 for comparison of TMS indicators) the effect was statistically significant and was not linked to decreased excitability in the resting state with the eyes closed. Thus, the greater increase in excitability on motor imagery with the eyes closed can be explained as a result of subjects' better concentration on the sensorimotor image in the absence of a visual information stream.

This result allows us to suggest that ideomotor training (used both in rehabilitating patients with poststroke movement disorders [Dijkerman et al., 2010] and with the aim of improving sporting performance in healthy people [Holmes and Calmels, 2008]) may be more effective with the eyes closed, and that vibrational stimulation is suitable for practical devices.

Comparison of classification speeds for two BCI paradigms. Vibrational stimulation in and of itself can generate somatosensory event-related potentials [Yao et al., 2014]. With the aim of evaluating the contributions of such EEG reactions to classifying motor imagery patterns, we compared the time dynamics of a posteriori probabilities of the classifier after delivery of stimuli in the new BCI paradigm (with vibrational delivery of stimuli with the eyes closed) with the classical version (visual stimulus encoding), as described in our previous report [Vasilyev et al., 2017].

Classification speed using vibrational stimulus delivery was no different from that observed with visual command encoding (this was 1.7–2 sec from the start of the stimulus in both cases), which shows that vibrational stimulation in the BCI presentation paradigm has no effect on the EEG patterns used for classification of mental states. Thus, vibrational stimulation can be used with success in BCI devices requiring rapid program responses.

This present study demonstrated that users can learn to operate in the BCI loop with the eyes closed and with vibrational delivery of coπmmands and feedback. The characteristics of EEG activity, corticospinal excitability, session-by-session dynamics, and the accuracy of BCI operation in this approach were at least no different from those in the classical scheme with visual stimulus delivery, and for some users the new paradigm had advantages in terms of a number of indicators. This BCI paradigm opens up potentials for use by people with poor vision and expands the variants for practical BCI devices (especially in tasks requiring constant attention to changing visual information).

Conclusions. A new brain–computer interface paradigm based on motor imagery in which stimuli to perform and feedback were delivered using vibration bracelets was developed and tested in 11 healthy volunteers. All subjects succeeded in assimilating the skill of motor imagery of the hands in the training regime with the eyes closed.

The characteristics of EEG patterns during motor imagery in this BCI corresponded to those in classical BCI based on visual encoding of commands and feedback: marked desynchronization of sensorimotor rhythms was seen, along with a learning effect.

Seven of the 11 users showed equal success in motor imagery of the hands with both closed and open eyes. Among those subjects with lower BCI classification effectiveness, two demonstrated better results with the eyes closed and two with the eyes open.

Motor imagery leads to increases in corticospinal excitability, this phenomenon being more marked with the eyes closed.

Vibrotactile stimulation delivered at the beginning of the motor imagery trial had no effect on the rate of reaching peak pattern recognition accuracy as compared with classical BCI based on visual stimuli.

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