Poor BCI Performers Still Could Benefit from Motor Imagery Training

Alexander Kaplan[1,2,3](✉), Anatoly Vasilyev[1,2], Sofya Liburkina[1,2], and Lev Yakovlev[1,3]

[1] Lomonosov Moscow State University, Moscow, Russian Federation
akaplan@mail.ru, a.vasilyev@anvmail.com
[2] Pirogov Russian National Research Medical University, Moscow, Russian Federation
[3] Lobachevsky State University of Nizhni Novgorod, Nizhni Novgorod, Russian Federation

Abstract. Nowadays, there is a growing number of studies suggesting that coupled with the brain-computer interface (BCI) the motor imagery practice could be a helpful tool in neurorehabilitation therapy, but the actual neurophysiological correlates of such exercise are poorly understood. In this study we examined two of the most notable neurophysiological effects of motor imagery – the EEG mu-rhythm desynchronization and the increase in cortical excitability assessed with transcranial magnetic stimulation (TMS). We have found that subjects' BCI performance was highly correlated with mu-rhythm features and was not associated with the cortical excitability increase. Subjects with the lowest accuracy in BCI all had a statically significant excitability raise during motor imagery and did not differ from better performers. Our results suggest that poor BCI performers with weak EEG response still could benefit from the motor imagery training, and in that case cortex excitability level had to be considered for the control measurement.

Keywords: Motor imagery · Brain-computer interface · Transcranial magnetic stimulation · Classification accuracy · Electroencephalogram · Cortical excitability · Mu-rhythm · Neurorehabilitation

1 Introduction

Motor imagery (MI) is most commonly defined as a mental rehearsal or mental representation of person's own body parts' movement. MI is considered to be helpful as a training technique for neurorehabilitation of people with different motor disabilities [1, 2]. Professional athletes and musicians claim to use motor imagery, also referred as «mental practice» , to improve their performance as well [3].

Motor imagery is known to promote patterns of the event-related desynchronization (ERD), or suppression, of mu-rhythm found in EEG over the sensorimotor areas of the human cortex. These patterns could be identified in an ongoing EEG and decoded into commands for external devices providing direct communication channel between the brain and the outer world. Such a technique is called a brain-computer interface (or BCI) and was originally designed for the severely disabled patients with the limited

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communication and motor capacities [4]. Recently, several new use cases for BCI are starting to emerge in both clinical and non-clinical application fields [5, 6].

It is believed that, in neurorehabilitation BCI approach promises an additional benefit for the motor imagery practice, because, firstly, it allows subject to learn the mental exercise by monitoring his or her own imagery quality, and secondly, promotes motivation for practice by creating an engaging feedback environment [7]. Moreover, detected MI could be translated into a command for a stimulating device (such as a functional electrical stimulation (FES) or an exoskeleton), which presumably complements the training by activating natural afferent pathways of sensorimotor system.

On the other hand, in order to work, MI-BCI requires a user to have a distinctive and consistent mu-rhythm response, which considerably varies among individuals, [8] and hence does not describe the motor imagery effort quality. Due to the weak or absent EEG response during MI, a substantial portion of the population is characterized as «BCI-illiterate» or «inefficient» indicating poor performance in a brain-computer interface circuit [9], and therefore those people are being eliminated from such activity. Although it is not clear to what extent BCI performance is determined by the user's capability to correctly perform motor imagery [10, 11], recent evidence suggests that individual neurophysiological [12] and anatomical [13] features play a significant role in MI-BCI aptitude. For training purposes, especially in a restricted and high-stakes clinical setting, it is important to establish whether the mu-rhythm reaction used in BCI happens to be a basic neurophysiological effect of MI (and therefore is connected with potential training efficiency) or rather mere manifestation of the motor-related mental activity with weak or absent relation to the target effect of training.

Another important neurophysiological effect of motor imagery is its ability to increase the excitability of primary motor cortex (M1) commonly assessed by the means of transcranial magnetic stimulation (TMS) [14]. Increasing cortex excitability, which translates into plasticity induction, is considered to be one of the most important goals of neurorehabilitation therapy and therefore appears to be a desirable effect of motor imagery practice. Nevertheless, very little research has been done to determine actual quantitative connection between excitability changes during motor imagery and other metrics such as BCI-performance and my-rhythm reaction. Takemi et al. in [15] have shown that the excitability and mu-rhythm desynchronization values are positively correlated within subjects on different trials, but it should be noted that, only subjects with noticeable ERD reaction participated in that study.

Considering the growing tendency to use BCI technology for motor imagery practice, it would be interesting to know whether high performance users are actually any different from the «BCI-illiterate» subjects in regard to MI-induced cortex excitability changes. Hence, the purpose of our research was to assess the connection between the user's BCI performance and the neurophysiological effects of motor imagery which are changes in EEG mu-rhythm amplitude and M1 cortex excitability.

2 Method

2.1 Subjects

18 healthy human subjects (6 females) participated in the experiment. There were no exclusion criteria other than neurological health. Hand dominance was assessed with the Edinburgh handedness questionnaire [16]: 15 of the subjects were right handed (score +0,875 ± 0,04), two – left handed (score −0,9 ± 0,00) and one – bimanual (score +0.1)). All of the participants gave their informed consent. The experimental procedure was approved by the Lomonosov Moscow State University Ethical Committee.

2.2 Sessions

Each subject participated in 5–8 motor imagery (BCI) sessions (experimental days) during the course of study. Some of the participants had previous MI-BCI-experience. Each BCI experimental session lasted 2–2.5 h. Last session comprised of the shortened BCI session protocol followed by the TMS measurement.

2.3 Motor Imagery Training

During regular sessions subjects were trained to perform kinesthetic motor imagery of sequential self-paced movements: II–V finger presses (flexion at metacarpophalangeal joint), II–V finger elevations (extension at metacarpophalangeal joint) and shoulder forward/backward circumduction (explained to subjects as «crawl stroke» from seated arm-down position). During motor imagery subjects were seated at a comfortable chair with their hands relaxed at armrests.

Subjects were asked to perform mental tasks on visual cues appearing on the LCD monitor in front of them. Icons with a depicted shoulder or fingers cued the specific motor imagery task and an abstract picture with lines and dots (or “visual scene”) cued the visual attention task, during which the subject was asked to count elements of that picture. Visual attention and motor imagery cues were presented for 6–8 s in a semi-random sequence with 2–3 s intervals (blank grey background). During the feedback runs an empty horizontal rectangular frame was presented below the pictogram of the task cue. Subjects were asked to fill the frame (progress bar animation) as much as possible using the cued mental state.

2.4 Signal Acquisition and Processing

EEG recording was performed with 64 active electrodes system (ActiChamp, Brain Products GmbH, Germany) positioned according to the modified IFCN «10 %-system» [17]: A1, A2 positions were replaced with FT9 and FT10 accordingly, and electrodes in CP9 and CP10 positions (mastoids) were used as a reference. Impedance for all electrodes was kept below 20 kΩ. Signal was sampled at 500 Hz and bandpass-filtered in 0,05–49 Hz band.

EMG was recorded with two pairs of Ag/AgCl hat-shaped electrodes («ED6» , EasyCap GmbH, Germany) from extensor digitorum communis (EDC) and flexor digitorum superficialis (FDS) muscles. The skin under the electrodes was prepared with an abrasive paper and alcohol cotton swabs, so that the impedance could be kept within 1.5–3 kΩ interval (except for 2 subjects with 10–15 kΩ due to the skin condition). Signal was digitalized at 10 kHz using the NVX-52 amplifier (MKS, Zelenograd, Russia) and filtered in 5–3500 Hz band with the 4th-order Butterworth digital filter.

2.5 BCI Classification

BCI2000 software [18] with a custom classifier module was used for data recording and feedback environment. Offline calculations were performed in MATLAB. In order to classify the two mental tasks (MI and visual scene task), the 62-channel EEG signal was first bandpass filtered in 4–40 Hz, using a 4th-order Butterworth filter, and then spatially filtered using the Common Spatial Pattern (CSP) filter [19], calculated on the initial calibration run with same mental states. The CSP-filtered signal was analyzed in spectral domain using the short-time Fourier transform (FFT in 1 s windows with 90 % overlap), and then the extracted spectral power in the user-specific channel and frequency band was classified using naïve Bayes classifier with 10 Hz output sampling rate. The initial classifier was calculated on the 10-trial calibration run before feedback runs and it was subsequently updated (fully recalculated) using the most current data throughout the session. During the feedback runs classifier output was translated into the horizontal progress bar animation. Numerical value of filling percentage was displayed at the end of each 6 s-trial.

2.6 TMS Measurement

Single-pulse TMS was applied with a figure-of-eight shaped coil (outer diameter of each coil: 7 cm) connected to a Neuro MS/D magnetic stimulator («Neurosoft» , Ivanovo, Russia). Hotspot for the right FDS muscle was determined and TMS output was set to elicit 0.4-0.8 mV MEP during resting condition (~110–115 % of motor threshold). TMS measurement was divided into 5 runs. On each run subject performed two types of mental tasks – one of three motor imagery tasks (experimental condition) and a visual attention task (reference condition). During one run the visual attention stimulus was changed to a blank screen. Mental task cues were presented in the sequence of 3 (AAABBBAAABBB…, 24 total) and during each of them TMS-pulse was delivered at random moment 2–5 s after the cue was displayed. 120 evoked responses were collected during TMS session in total (by condition: 36 – fingers flexion imagery, 12 – fingers extension imagery, 12 – shoulder circumduction imagery, 48 – visual attention state, 12 – blank screen). During TMS measurement online EMG-feedback was displayed at the right side of the screen as vertical bar with the real-time RMS (root-mean-square) value (300 ms window, 100 ms step). Participants were asked to find the hand position with minimal ongoing EMG amplitude and maintain the corresponding bar level constant during the whole run.

2.7 Data Analysis

For EEG patterns analysis only data from last two sessions were used. An average mu-rhythm ERD score was calculated as a percentage of the overlap between distribution of power spectra value of user-specific power band for two mental states – the motor imagery state and the visual attention state. The value was extracted from the peak ERD electrode location of the left hemisphere (typically, C3-position). In order to mitigate volume conduction effects and improve signal-to-noise ratio of individual electrodes, Surface Laplacian filter [20] was applied to the raw EEG signal.

BCI performance was evaluated for each subject on 100-trial (6 s/trial) sample with 50 trials per class (the motor imagery of right fingers flexion and the visual scene task). Classification accuracy was calculated as a percentage of correct classification time, which is the same as the average feedback score displayed for a subject.

Amplitude of motor-evoked potentials was measured peak to peak (between negative and positive phases of potential). Potentials with any signs of raised muscular activity during preceding 1000 ms interval were rejected by hand. MEPs in experimental condition (motor imagery) were normalized to mean amplitude of the reference condition («visual attention» or blank screen) on the same run.

3 Results

3.1 Classification Accuracy

BCI performance for all subjects was measured on 100-trial sample: 60 trials were extracted from the last session (same day as TMS-measurement) and 40 trials from the previous session. Each trial consisted of 6 s EEG recording, where subject was performing either a motor imagery of right fingers flexion or a «visual scene» task.

All of the participants achieved classification accuracy above chance level of 0.5 for two classes. Mean accuracy was 0.85, SD = 0.078, ranging from 0.68 to 0.96. Subjects

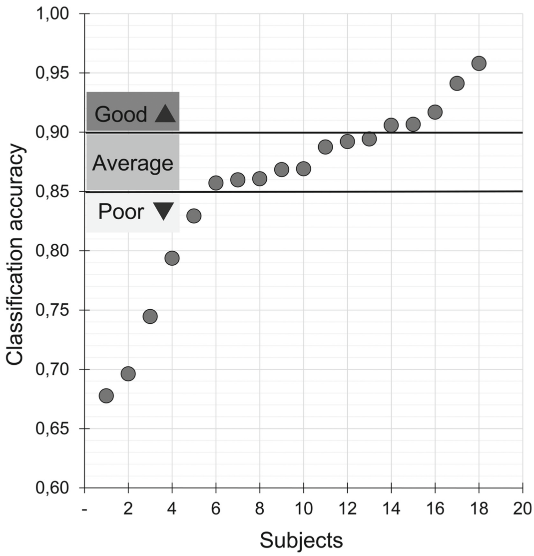

Fig. 1. Classification accuracy of all subjects measured on 100-trial sample

were assigned to one of the three categories according to their performance: poor (N = 5), average (N = 8) and good (N = 5) performers (Fig. 1).

3.2 Mu-rhythm Patterns

Mu-rhythm EEG patterns were evaluated for all the subjects using using the same 100-trial sample as for the classification accuracy measurements. Spectral changes in a subject-specific frequency band were calculated for the motor imagery state compared to the «visual scene» task that was used as a reference state. Raw EEG signal was filtered with Surface Laplacian and then spectral power values' distributions (FFT) were analyzed for both states for each channel and frequency. The distance between power values distributions was expressed as overlap percentage («ERD score») for each EEG channel. Subject's ERD score was chosen as the maximum single-electrode value at left sensorimotor area (electrodes FC5, FC3, FC1, C5, C3, C1, CP5, CP3, CP1).

A topographical representation of the average ERD score heatmap for all subjects is shown at Fig. 2 (right). Peak desynchronization was observed over C3-CP3 electrodes with symmetrical weaker activation over C4-CP4. For some of the subjects, frontal (electrodes F-Fc) desynchronization accompanied the reaction over sensorimotor cortex.

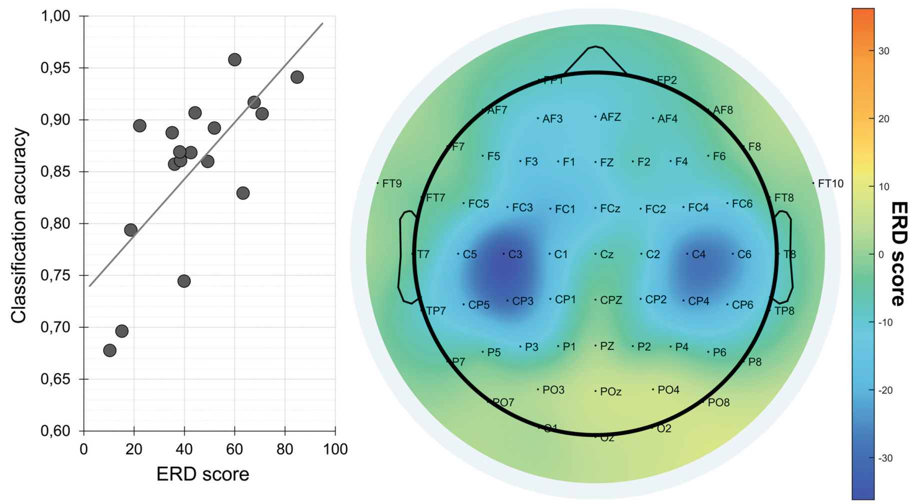

Fig. 2. **Left** – Correlation of ERD scores with BCI classification accuracy, each dot represents one subject, the solid line depicts linear regression. **Right** – Topographical representation of mean spectral changes during motor imagery (n = 18). Negative values (blue) represent decrease in mu-rhythm power (desynchronization) and positive values (orange) represent increase in mu-rhythm power (synchronization). (Color figure online)

Strong correlation (Pearson's r) of 0.71 ($p < 0.05$) was observed between classification accuracy and subject's ERD score (Fig. 2, left). Three of the subjects from the poor-performers group had the lowest ERD score below 20, indicating the absence of mu-rhythm reaction.

3.3 Cortex Excitability Measurement

Cortex excitability was assessed through TMS measurement performed at the end of the last experimental session of each subject. Motor evoked potentials (MEPs) were

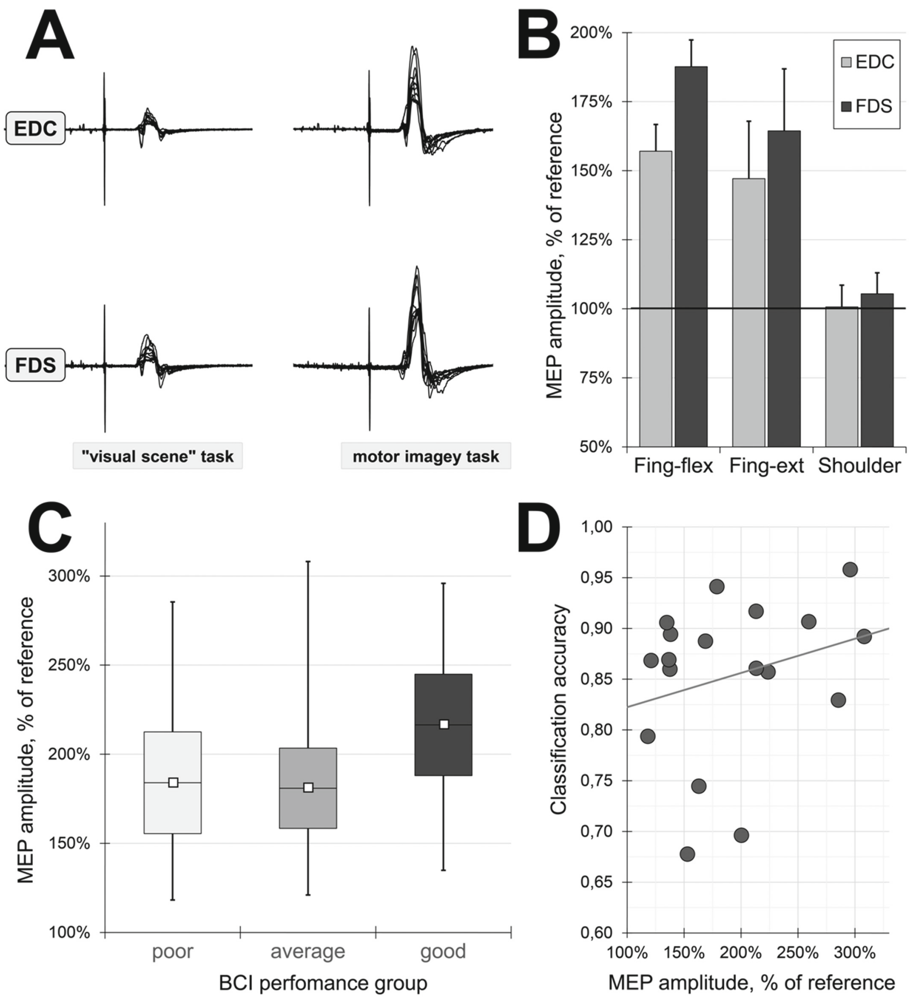

Fig. 3. **A** – Example of MEPs from FDS and EDC muscles during motor imagery and «visual scene» task acquired from one of subjects. **B** – Amplitude increase of MEPs in FDS and EDC muscles during three types of motor imagery for all subjects (n = 18). Mean values are shown with standard error indicated by whiskers, the solid line represents mean MEP amplitude in the reference condition. **C** – Amplitude increase of MEPs in FDS during motor imagery of fingers flexion imagery for subjects of three BCI performance groups. Square dots indicate mean values, boxes – standard error and «min-max» range is shown by whiskers. **D** – Correlation of MEPs amplitude increase with classification accuracy, each dot represents one subject, the solid line depicts linear regression.

collected in response to the suprathreshold transcranial magnetic stimulation of motor cortex (EDC muscle hotspot) during «visual scene» task and three of motor imagery states (fingers flexion, fingers extension, shoulder circumduction). Two of the muscles were monitored: extensor digitorum communis (EDC) and flexor digitorum superficialis (FDS). All MEPs were normalized to the mean values during the referential «visual scene» task, collected from the same muscle within the same recording sequence.

Motor imagery of both fingers movements resulted in a statistically significant (ANOVA, $p < 0.05$) MEPs amplitude increase (Fig. 3-B) in both muscles with mean values ranged from 157 % to 188 % of the referential state. Shoulder circumduction imagery didn't lead to statistically significant MEPs changes in either muscle.

Analysis of EDC MEPs during an imagery of the finger flexion revealed a significant variation between subjects. For all of the subjects the amplitude increase during imagery was statistically insignificant (Mann–Whitney U test, $p > 0.05$) and varied from 118 to 306 % of the referential state. MEPs increase did not correlate either with BCI classification accuracy (Pearson's $r = 0.27$) or with ERD score (Pearson's $r = 0.32$).

4 Discussion

4.1 BCI Performance

In the current research we have investigated only two-class BCI performance, whereas most of the research in this area is being concentrated on high-performance multiclass settings [21]. Our intention in that regard was to bring the experimental design of BCI training sessions closer to what is expected in clinical application: a simplified setting with fewer commands, short and regular training sessions.

In our research the group classification accuracy level was fairly high (85 %) compared to similar studies [22]. That happened because all of our subjects participated in at least five BCI training session, whereas in most of the other research performance was measured based on the single and often prolonged session using naïve subjects. Another reason for the increased accuracy is the use of a non-motor mental task with motor imagery. Previous research demonstrates that the choice of pairing mental states is of great importance for a good and consistent accuracy level [23].

4.2 Mu-rhythm Desynchronization

In this study for the majority of subjects we have observed patterns of desynchronization of bilateral structure, which is in accordance with our previous research [24] and backed up by several other studies [25, 26]. For the single motor imagery task recognition bilateral structure of the patterns allows to construct more robust spatial filter (CSP, [19]), which improves classification accuracy.

As was expected, mu-rhythm desynchronization magnitude was positively correlated with BCI-accuracy. That confirms our subjects used modulation of sensorimotor rhythms for BCI control. For patterns classification of subjects with a weak or absent ERD reaction (ERD score below 20) P-PO channels were dominant in the individual spatial filters indicating involvement of occipital alpha rhythm which is non-specific to the motor imagery task. Those subjects are most likely to be deemed as «BCI-illiterate» in regard of multiclass motor imagery setting, although in simplified our two-class BCI environment they yielded satisfactory results.

4.3 Cortical Excitability

When investigating cortical excitability changes, we have observed that motor imagery of fingers movement has led to statically significant increase in motor cortex excitability in both of the forearm muscles. We have not found clear EDC and FDS muscle differentiation in corresponding fingers movements – extension and flexion, often reported in similar studies [27]. In our opinion the main reason why it was happening is that it was quite hard to differentiate between the kinesthetic images of sequential upward and downward movements of fingers, since they share most of the perceived proprioceptive sensations. Indeed, as was expected, we observed no MEPs amplitude raise in forearm muscles for a shoulder movement, which is completely unrelated to fingers.

The MEPs amplitude increase was not correlated with either BCI accuracy or ERD reaction. Although subjects with the best BCI performance (and hence the strongest mu-rhythm ERD) tended to have higher increase in cortical excitability, statically significant difference was not observed.

Our results could be explained as a contribution of two reasons. First one relates to the properties of the measurements. Mu-rhythm power decreases during motor imagery. and thereby its modulation range is limited by the resting-state power value [12], which varies both in the general population and within subjects on different experimental days. That is why the subjects whose resting mu-rhythm power is closer to the noise level (undetectable amount) generally demonstrate poor BCI-performance. On the contrary, M1 excitability level increases during motor imagery and therefore has a greater measurable range.

The second explanation lies in the physiological nature of the measurements. Mu-rhythm appears to be an indicator of the general inhibitory input into the vast cortical areas, whereas M1 excitability reflects the state of the local neuron group corresponding to a discrete muscle. Based on prior knowledge, motor imagery should promote excitability of local cortical pathways involved in the imagined movement, but not necessarily alter the general inhibitory output of thalamocortical circuits.

Those explanations do not contradict with previous findings, published in [15, 28], since our conclusions address the intersubject level, while mentioned papers describe with-subject correlations. Taken together these results could be evidence that motor imagery involves several interconnected but separate sensorimotor pathways and different assessment strategies are needed for their exploration.

5 Conclusion

Our results suggest that if motor imagery practice is considered to be beneficial in regard to training discrete motor cortex pathways, poor BCI performance should not discourage users from mental exercises. EEG control should be accompanied by other cortex excitability measurements such as TMS to provide a more comprehensive estimate of physiological impact of the training.

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