Resubmission: Regular Article for NeuroImage

Submitted on 8th July 2014, Editor: Dr. Hartwig Roman Siebner

Neuroanatomical correlates of brain-computer interface performance

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Abstract

Brain-computer interfaces (BCIs) offer a potential means to replace or restore lost motor function. However, BCI performance varies considerably between users, the reasons for which are poorly understood. Here we investigated the relationship between sensorimotor rhythm (SMR)-based BCI performance and brain structure. Participants were instructed to control a computer cursor using right- and left-hand motor imagery, which primarily modulated their left- and right-hemispheric SMR powers, respectively. Although most participants were able to control the BCI with success rates significantly above chance level even at the first encounter, they also showed substantial inter-individual variability in BCI success rate. Participants also underwent T1-weighted three-dimensional structural magnetic resonance imaging (MRI). The MRI data were subjected to voxel-based morphometry using BCI success rate as an independent variable. We found that BCI performance correlated with gray matter volume of the supplementary motor area, supplementary somatosensory area, and dorsal premotor cortex. We suggest that SMR-based BCI performance is associated with development of non-primary somatosensory and motor areas. Advancing our understanding of BCI performance in relation to its neuroanatomical correlates may lead to better customization of BCIs based on individual brain structure.

Keywords

brain-computer interface; BCI performance; event-related desynchronization; motor cortex; motor imagery; voxel-based morphometry

Abbreviations

BCI, brain-computer interface; PMd, dorsal premotor cortex; EEG, electroencephalography; ERD, event-related desynchronization; MRI, magnetic resonance imaging; MIQ-R, revised movement imagery questionnaire; SMA, supplementary motor area; SMR, sensorimotor rhythm; SSA, supplementary somatosensory area; VBM, voxel-based morphometry

1. Introduction

Brain-computer interfaces (BCIs) have been studied for their applicability to neuroprostheses as well as a possible neural therapy to induce beneficial plastic changes for rehabilitation (Shindo et al., 2011). Studies have demonstrated the efficacy of motor imagery-induced event-related desynchronization (ERD) of the mu rhythm, or sensorimotor rhythm (SMR), in controlling electroencephalography (EEG)-based BCIs (McFarland et al., 1997; McFarland et al., 2005; Neuper et al., 2006; Pfurtscheller et al., 2006). The SMR is an alpha-range EEG oscillation recorded from the central areas, and its ERD is induced by motor execution, motor imagery, or motor observation (Neuper et al., 2005).

Although the SMR-based BCI is one of the most widely used non-invasive BCIs, performance varies considerably between individuals as well as between sessions by the same individual (Wolpaw et al., 2002). Only a handful of studies have investigated correlates of inter- and intra-individual variability in BCI performance. Function-based predictors of BCI performance include SMR amplitude at rest (Blankertz et al., 2010) and concentration level (Hammer et al., 2012). Using functional magnetic resonance imaging (MRI), BCI performance has also been found to correlate with activity in supplementary motor and prefrontal areas during a motor imagery task (Halder et al., 2011). This finding is consistent with neurophysiological studies showing that non-primary motor areas are involved in motor preparation and/or planning (Hoshi and Tanji, 2004). It is also consistent with previous neuroimaging studies on motor imagery, which revealed the premotor-parietal network to be an underlying substrate of motor imagery and motor planning (Hanakawa et al., 2008; Hanakawa et al., 2003).

Structural measures from brain MRI may also offer a means to predict BCI performance. In fact, fractional anisotropy derived from diffusion tensor MRI for the cingulum, superior fronto-occipital fascicle, and corpus callosum have shown efficacy in predicting BCI performance (Halder et al., 2013). Moreover, burgeoning evidence indicates that inter-individual variability of performance in cognition (Frangou et al., 2004; Maguire et al., 2000), language (Hosoda et al., 2013), and movement (Steele et al., 2012; Tanaka et al., 2013) correlate with gray matter volume in an ability-specific manner, although correlation of gray matter volume with BCI performance has yet to be identified. Based on these previous findings, we hypothesized that gray matter volume, especially that of non-primary motor and prefrontal areas (Halder et al., 2011), could be used to predict BCI performance. To test this hypothesis, we performed a whole-brain voxel-based morphometry (VBM) (Ashburner and Friston, 2000) analysis on healthy participants and examined the relationship between performance using an SMR-based BCI and gray matter volume.

2. Methods

2.1 Participants

Thirty healthy adults (14 males and 16 females, mean age $\pm$ standard deviation: 22.4 ± 3.1 years) participated in this study. All participants were right-handed as assessed by the Edinburgh Inventory (Oldfield, 1971), had normal or corrected-to-normal vision, reported no history of neurological or psychological disorders, and had no prior experience using BCIs. All participants gave informed consent before the experiment according to the study protocol approved by the ethics committee of the National Center of Neurology and Psychiatry. Motor imagery ability was assessed with a Japanese translation of the revised Movement Imagery Questionnaire (MIQ-R) (Hall and Martin, 1997).

2.2 EEG acquisition

Electrophysiological data were acquired using BrainAmp amplifiers and an EEG cap (Brain Products, Gilching, Germany) consisting of 12 electrodes, nine positioned over the sensorimotor area (F3, F4, C3, C4, Cz, P3, P4, T7, and T8), one over the left eye (Fp1), one for ground (AFz), and one for reference (FCz). Electrode impedances were kept below 15 k Ω , excluding 10 k Ω of resistance built into the system. To rule out potential influence by overt movements, electromyograms (EMG) over the left and right thenar eminences and horizontal electrooculograms (EOG) were also simultaneously acquired. Data were sampled at 5000 Hz and filtered with 0.1-Hz highpass and 250-Hz lowpass hardware filters. A 1-23 Hz bandpass filter (12th order elliptic) was then applied in software to reduce high-frequency noise and baseline drift. The EEG data were fed into BCI2000 software, which was used to control the experiments (Schalk et al., 2004).

2.3 BCI experiment

Participants underwent a BCI experiment in which visual feedback was provided online (Fig. 1A). During each trial, a red rectangular target appeared in the lower right, lower left, or entire bottom portion of the display, signifying a Right trial, Left trial, or control trial, respectively. After 1 s, a cursor appeared horizontally centered at the top of the screen and immediately began falling at a constant rate, such that it would reach the bottom in 4 s. During the Right and Left trials, participants were instructed to perform imagery of finger-thumb opposition with the right and left hands, respectively, to control the horizontal positioning of the cursor so that it would hit the target at the bottom. Participants were instructed to use, to best of their ability, kinesthetic rather than visual imagery (Neuper et al., 2005). They also practiced the movements

in response to the cues overtly before engaging in the experiment. During the control trials, participants were asked to passively watch the visual cues on the display. During this period, participants continuously received visual feedback from the falling cursor in all trials. A 1-s result presentation interval followed, during which the cursor and target would turn yellow in the case of a successful trial, or remain unchanged otherwise. After a 1-s inter-stimulus interval with a blank screen, the next trial would begin. Trials were organized in a block design (Fig. 1B), with each block consisting of three trials of the same task. A run consisted of 11 pseudo-random permutations of Right and Left blocks interleaved with 12 control blocks (33 Right trials, 33 Left trials, 36 control trials). Each run began and ended with a control block. The first block of each task was used for initialization of BCI2000's normalization transform (McFarland et al., 2011) and discarded, leaving a total of 30 Right, 30 Left, and 33 control trials per run. Participants performed two runs: one practice run followed by one test run. Each run lasted 12 minutes. Between runs, participants were allowed to take a break for a few minutes. Further analyses were performed on results from the test run, unless otherwise indicated. BCI success rate was calculated from the number of right-target and left-target hit trials over all Right and Left trials.

2.4 Online EEG processing

EEG data were downsampled to 500 Hz, and electrodes over the sensorimotor area were re-referenced to large Laplacian derivations for the C3 and C4 electrodes. Spectral amplitudes for C3 and C4 were then computed using autoregressive estimation (Marple, 1987; McFarland et al., 1997) with a window length of 500 ms and a bin width of 3 Hz. For the BCI experiment, we selected the 9.5-12.5 Hz bin for feature extraction in all participants, allowing the BCI to be controlled with SMR spectral amplitude (Pfurtscheller and Lopes da Silva, 1999). We decided to use this single, predetermined alpha frequency band for BCI control through several pilot measurements in which we consistently found imagery-related ERD for our BCI system. A control signal for cursor movement was computed from the difference in SMR amplitudes for C4 and C3, where greater ERD in C4 resulted in leftward cursor movement and greater ERD in C3 resulted in rightward cursor movement online.

2.5 post-hoc EEG analysis

After the online BCI experiment, a post-hoc offline analysis was performed to calculate EEG spectral amplitude, ERD percentage, peak ERD frequency, and ERD laterality. Spectral amplitude was calculated in 3-Hz wide frequency bins centered at 5, 8, 11, 14, 17, 20, and 23 Hz. ERD percentage was calculated as the percent difference between task and control SMR amplitudes. Peak ERD frequency was defined as the frequency bin yielding the greatest

amplitude difference between imagery and control tasks. ERD laterality was calculated as the difference between C3 and C4 ERDs for each trial. Additionally, to determine if participants could control the BCI by modulating their C3 and C4 SMR amplitudes, we tested for correlation between BCI success rate and ERD laterality at 9.5-12.5 Hz.

2.6 MRI acquisition

Structural MRI data were acquired on a different day within one week (1.63 ± 1.33 days) of the BCI experiment. We used a 3T MRI scanner (Magnetom Trio, Siemens, Erlangen, Germany) and an 8-channel phased array receiver coil in accordance with our previous VBM study (Hosoda et al., 2013). T1-weighted imaging acquisition was performed using a three-dimensional magnetization prepared rapid acquisition gradient echo sequence (repetition time = 2000 ms, echo time = 4.38 ms, inversion time = 990 ms, voxel size = $1 \times 1 \times 1$ mm, flip angle = 8° , bandwidth = 130 Hz/px, field of view = 192×176 mm).

2.7 Voxel-based morphometry

We used VBM to investigate correlation of BCI performance with gray matter volume in the whole brain. Preprocessing and analyses of T1-weighted MRI data were done using VBM8 Toolbox (<http://dbm.neuro.uni-jena.de/vbm.html>) implemented in SPM8 (<http://www.fil.ion.ucl.ac.uk/spm>). Raw images were segmented into gray matter, white matter, and cerebrospinal fluid images in the native space. Segmented gray matter images were normalized to the study-specific gray matter template using diffeomorphic anatomical registration through exponentiated Lie algebra (Ashburner, 2007). These images were modulated with a Jacobian determinant. The normalized images were further transformed to the Montreal Neurological Institute template in standard stereotactic space, and spatially smoothed using a Gaussian kernel of 12 mm full-width at half-maximum. We performed multiple-regression analyses for BCI success rate as the independent variable, with sex, age, total intracranial volume, MIQ-R score, and SMR amplitude during the control trials as nuisance variables. MIQ-R score and control trial SMR amplitude were used to exclude effects of inherent ability related to motor imagery skill and resting SMR amplitude (Blankertz et al., 2010; Cremades and Pease, 2007). For BCI success rate, we used data from the BCI test run and double-checked the results using those from the practice run. We also performed separate multiple-regression **whole-brain** analyses for MIQ-R and SMR amplitude, each implemented as the independent variable using SPM8. However, MIQ-R and SMR amplitude did not have normal distributions ($p < 0.05$ for all by Kolmogorov-Smirnov test). Hence, T1-weighted images were subjected to VBM analysis with SnPM (<http://warwick.ac.uk/snpm>) using these indexes as independent variables, and the results were confirmed using parametric analysis with

SPM8. Voxel-wise significance was set at a height threshold of $p < 0.05$ family-wise error corrected for multiple comparisons for the whole-brain search, using Gaussian random field theory (Friston et al., 1994).

3. Results

3.1 EEG-BCI online success rate

BCI success rate averaged across all participants' test runs was $71.1 \pm 13.3\%$ (range = 41.7 - 93.3). Testing for practice effects on BCI performance, we found that BCI success rate for the test run did not differ from that of the practice run (mean success rate = $70.7 \pm 14.0\%$, range = 43.3 - 93.3%) using a paired t-test ($p = 0.76$). Twenty participants controlled the BCI with a success rate significantly above chance (two-tailed exact binomial test, 99.5% confidence interval) in both the test run and the practice run. The remaining 10 participants were not able to control BCI above chance in either run, though none did significantly worse than chance. Consistent with these findings, BCI success rates for the practice and test runs were strongly correlated ($r = 0.81$, $p < 0.0001$). These results indicate that the present BCI success rate reflects an inherent, rather than trained or non-EEG based, ability for BCI control.

3.2 Offline analysis of neurophysiological data

No statistical differences were found between Left, Right, and Rest tasks for any EOG or EMG channels (repeated measures ANOVA, $n=30$, $p > 0.1$ for each channel), ruling out influence of muscle or oculomotor activity on the success rate.

In an offline analysis of EEG data, peak ERD frequency averaged across all participants occurred at the 11 Hz bin (9.5-12.5 Hz; Fig. 2A) while individual peaks ranged from 5 to 17 Hz (Fig. 2B). Subjects with peaks at 5 or 17 Hz showed wide ERDs spanning 5 to 20 Hz, and subjects with peaks at 14 Hz also showed ERDs at 11 Hz. Three subjects showed nearly nonexistent ERDs, or rather event-related synchronization (ERS), during the BCI task. Despite the variability of the ERD peaks, no significant difference in BCI success rate was found between subjects with 11-Hz peak ERDs and subjects with peak ERDs at other frequencies for either the Right task (mean success rate = $78.3 \pm 13.4\%$ for 11-Hz peak ERDs at C3 and $71.2 \pm 16.5\%$ for other peak ERDs, $p = 0.231$) or the Left task (mean success rate = $75.3 \pm 18.4\%$ for 11-Hz peak ERDs at C4 and $66.9 \pm 16.7\%$ for other peak ERDs, $p = 0.234$; two-sample t test). However, ERD laterality at the 11 Hz bin significantly correlated with BCI success rate in both Right ($r = 0.62$, $p < 0.01$) and Left ($r = -0.71$, $p < 0.01$) trials as Pearson's correlation after Bonferroni correction for multiple comparisons (Fig. 3). These findings reasonably show that control of the BCI depended upon ERD laterality at

9.5-12.5 Hz.

3.3 Gray matter volume

VBM analysis using SPM8 revealed correlations of individual variability in BCI performance with anatomical structure of the motor-related cortical areas. We found positive correlations between BCI success rate and gray matter volume in the rostral part of the left dorsal premotor cortex (pre-PMd; $x, y, z = -26, 2, 45$; $T = 6.57$), right supplementary motor area (SMA; $x, y, z = 12, -15, 69$; $T = 5.98$), and right supplementary somatosensory area (SSA; $x, y, z = 11, -46, 54$; $T = 5.96$) ($p < 0.05$, family-wise error corrected) (Fig. 4). No areas showed negative correlation with BCI success rate. We performed additional analyses with both SPM8 and SnPM to exclude the possibility that the VBM findings reflected correlation with general motor imagery ability or resting SMR amplitude, at least in part. However, neither MIQ-R score nor control trial SMR amplitude correlated with gray matter volume in any areas of the brain.

4. Discussion

Neural Correlates of BCI Performance

The present study revealed anatomical structure of the premotor-parietal network to be an effective predictor of BCI control performance. We found that BCI control performance was higher in participants with greater gray matter volume in the SMA, SSA, and pre-PMd. The SMA, SSA, and PMd (including pre-PMd) form a mutually interconnected anatomical network (Bakola et al., 2013; Morecraft et al., 2004). The SMA and PMd, in particular, are well known as the substrates of motor imagery and motor planning (Hanakawa et al., 2008; Hanakawa et al., 2003). Particularly, Hanakawa et al. (2003) showed correlation of motor imagery performance with magnitude of activity in the comparable premotor-parietal network. The SSA has also been shown to be involved in motor preparation and/or planning (Li and Cui, 2013). In the study by Halder and colleagues (2011), high BCI performers showed greater prefrontal cortical activity during motor imagery than low BCI performers, suggesting the involvement of working memory in guiding and monitoring BCI performance. The prefrontal cortex is anatomically and functionally connected with the pre-PMd shown in the present study (Abe and Hanakawa, 2009; Abe et al., 2007), and the pre-PMd is suggested to play a hub-like role in bridging cognition and motor behaviors (Hanakawa, 2011). Taken together, it is likely that BCI performance relies on interactions between cognitive and motor functions. Therefore, it is plausible that the prefrontal-premotor-parietal network relevant to cognitive operation and motor planning underlies control of BCIs using motor imagery-based SMR modulation.

Methodological Considerations and Study Limitations

Mounting evidence has shown that gray matter volume correlates with a variety of human abilities (Frangou et al., 2004; Maguire et al., 2000; Tanaka et al., 2013) and also with neuroplastic changes associated with learning (Draganski et al., 2004; Hosoda et al., 2013). Hence, the correlation between gray matter volume and BCI success rate could be induced by BCI practice. However, the analyses of BCI performance during both the practice and test runs argue against the effects of learning on the present VBM findings. It was more likely that the gray matter volume in the motor-related areas was correlated with an inherent BCI performance. This is intriguing because all the participants were naive to any type of BCI. In this regard, the present study may offer insight towards understanding the neural correlates of ability to cope with the “first experience” of a new technology.

We used a single, predetermined alpha frequency band (9.5-12.5 Hz) for BCI control in all participants. We adopted this frequency band through several pilot measurements in which we consistently found imagery-related ERD in this frequency band for the use of our BCI system. We also reasoned that brain mechanisms related to imagery-related ERDs could possibly vary, depending upon the frequency band of ERDs. The consistent use of the same alpha frequency band might have helped to assess homogenous neural mechanisms related to SMR-based BCIs. Additionally, we applied a 1-23 Hz bandpass filter for removal of high-frequency noise, as well as for consistency with our closely related study using simultaneous EEG-functional MRI, which was presented in an abstract form (DaSalla, 2012). This methodology precluded using high beta frequencies as an EEG feature. Testing a different band, such as beta, would require new experimental conditions, and this was beyond the scope of the present study. In the event, post-hoc EEG analyses showed that the peak ERD frequency averaged across all subjects did occur at 9.5-12.5 Hz, but individual peak ERD frequency varied, implying that 9.5-12.5 Hz might not always be the optimal band for the detection of ERD.

However, the strong correlation between ERD laterality and BCI success rates (see Fig. 3) indicated that high BCI performers generated strong lateralization of ERDs during BCI trials. We thus considered that an ability of generating laterality to the SMR amplitude primarily determined the present BCI performance, which would be less vulnerable to variability in SMR peak frequency in comparison with BCIs using simple detection of SMR desynchronization. Participants with high BCI success rates might have used the feedback information to adapt their motor imagery performance for generating ERD laterality. We note that the present findings should be considered within the constraints of the experimental condition; namely, it is possible that different experimental strategies for EEG feature selection might result in disclosing different neural correlates of BCI performance.

Predicting BCI Performance

Though BCIs offer considerable potential in rehabilitation (Shindo et al., 2011; Wolpaw et al., 2002), BCI performance varies between users, the reasons for which are poorly understood. Understanding of neural mechanisms underlying individual variability of BCI performance will enhance development of BCIs and their application. In the present study, BCI success rate did not correlate with MIQ-R, which was expected to reflect a subjective aspect of motor imagery ability. This discrepancy meant that subjective assessment of motor imagery ability was not always a reliable marker of BCI performance. MIQ-R may reflect imagery-related functions in parieto-occipital regions (Cremades and Pease, 2007), located posterior to the motor-related areas shown here.

We may be able to use an objective measure of anatomofunctional properties of the brain for predicting BCI performance. In fact, Blankertz et al. (2010) showed that resting SMR amplitude correlated with BCI success rate, and Halder et al. (2011) found that activity in the supplementary motor and prefrontal areas during motor imagery correlated with BCI performance in participants with high SMR amplitude. More recently, Halder et al. (2013) showed that fractional anisotropy in the corpus callosum positively correlated with BCI-performance. Here we have added new evidence that another structural measure, gray matter volume of non-primary motor and somatosensory areas, can also be used to predict SMR-based BCI performance. Indeed, considering that the aforementioned function- and structure-based predictors for BCI performance were observed in relation to similar motor imagery tasks, they may be complementary or possibly even linked. Further investigation is needed to fully clarify the relationship among the BCI predictors relating to BCI performance.

5. Conclusion

In this study, we found that gray matter volume in motor-related cortical areas correlated with BCI success rate, providing a neuroanatomical index for BCI performance. Advancing our understanding of BCI control in relation to its neuroanatomical correlates may allow for better customization of BCIs based on individual brain structure. For example, such findings may lead to the emergence of “made-to-order” BCIs designed to utilize regions with high gray matter volume. This, in turn, may lead to greater usability for BCIs in real-world applications.

Acknowledgments

We thank Dr. Hideki Hoshino, Mr. Atsushi Nishimoto, and Dr. Yosuke Ogata for technical assistance and helpful discussions. This study was supported by PRESTO under the Japan

340 Science and Technology Agency, the Strategic Research Program for Brain Science by MEXT,
341 and KAKENHI grant (13423021) from MEXT.

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Figure legends

Figure 1: BCI experiment paradigm. **A**, Visual stimuli and durations for an example Left (L) trial. **B**, An example trial order for the three tasks. ISI: interstimulus interval, R: Right, C: visuospatial control.

Figure 2: **A**, EEG spectral amplitudes at C3 and C4 for each task, averaged across subjects. Grey shaded areas: SMR band (9.5-12.5 Hz), a.u.: arbitrary units. **B**, ERD percentage (bars) and histogram of peak ERD frequencies (lines) in C3 during Right trials (Red) and C4 during left trials (Green). Error bars: standard error.

Figure 3: Correlation between BCI success rate and ERD laterality in both Left trials and Right trials.

Figure 4: Correlation between BCI success rate and gray matter volume for the supplementary motor area (SMA), supplementary somatosensory area (SSA), and dorsal premotor cortex (PMd). Average gray matter volume was calculated from 10-mm spherical volumes of interest in the SMA (x, y, z = 12, -15, 69), SSA (x, y, z = 11, -46, 54), and PMd (x, y, z = -26, 2, 45) based on whole-brain analysis. **Voxel-wise significance was set at $p < 0.05$ family-wise error corrected for multiple comparisons.**

Figure 1

Figure 2

Figure 3

Figure 4