

Bridging the gap between motor imagery and motor execution with a brain–robot interface



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ABSTRACT

According to electrophysiological studies motor imagery and motor execution are associated with perturbations of brain oscillations over spatially similar cortical areas. By contrast, neuroimaging and lesion studies suggest that at least partially distinct cortical networks are involved in motor imagery and execution. We sought to further disentangle this relationship by studying the role of brain–robot interfaces in the context of motor imagery and motor execution networks.

Twenty right-handed subjects performed several behavioral tasks as indicators for imagery and execution of movements of the left hand, i.e. kinesthetic imagery, visual imagery, visuomotor integration and tonic contraction. In addition, subjects performed motor imagery supported by haptic/proprioceptive feedback from a brain–robot–interface. Principal component analysis was applied to assess the relationship of these indicators. The respective cortical resting state networks in the α -range were investigated by electroencephalography using the phase slope index.

We detected two distinct abilities and cortical networks underlying motor control: a motor imagery network connecting the left parietal and motor areas with the right prefrontal cortex and a motor execution network characterized by transmission from the left to right motor areas. We found that a brain–robot–interface might offer a way to bridge the gap between these networks, opening thereby a backdoor to the motor execution system. This knowledge might promote patient screening and may lead to novel treatment strategies, e.g. for the rehabilitation of hemiparesis after stroke.

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Introduction

Following a stroke, the ability of motor execution and motor imagery can be preserved or impaired independently of each other (de Vries et al., 2011; Wiese et al., 2005). Motor imagery can be understood as the planning of a movement, with its overt execution being inhibited. However, both tasks result in very similar power perturbations of oscillations in the α -range (8–14 Hz) and β -range (15–30 Hz) in identical brain areas (Decety, 1996; Ehrsson et al., 2003; Gao et al., 2011; Jeannerod, 1995; Kaiser et al., 2011; Miller et al., 2010). On the basis of these findings, Sharma (2006) has suggested that motor imagery training may serve as a backdoor to the rehabilitation of motor control, which is becoming increasingly important in the rehabilitation of severe upper limb hemiparesis following stroke (Ietswaart et al., 2011;

Langhorne et al., 2009). Brain–computer interfaces controlled by event-related power perturbations have been used to support motor imagery training with visual or auditory feedback (Ang et al., 2011; Kaiser et al., 2011). The combination of motor imagery and feedback with robotic rehabilitation (Hogan and Krebs, 2011; Lo et al., 2010), i.e. employing a brain–robot–interface with haptic feedback (BRI), is the most recent development in this field and has already been shown to be feasible and effective (Gomez-Rodriguez et al., 2011; Ramos-Murguialday et al., 2013). There is, however, still large heterogeneity in healthy subjects and stroke survivors as regard to their ability to control EEG power in the α - or β -range during a motor imagery task (Buch et al., 2012; de Vries et al., 2011; Vidaurre and Blankertz, 2010). Furthermore, from a network perspective, different networks have been implicated in motor imagery versus motor execution, casting some doubt on the idea of using motor imagery effectively for motor rehabilitation. To be specific, planning of manual actions of either hand involves the left posterior parietal and left motor areas (Creem-Regehr, 2009; Haller et al., 2009; Johnson-Frey et al., 2004; Lewis, 2006; Rushworth et al., 2003), whereas execution of hand movements engages a bilateral network between the motor areas of both hemispheres

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(Grefkes et al., 2008; Shibasaki, 2012), with the final descending pathway originating from the contralateral primary motor cortex (Chouinard and Paus, 2006).

Motivated by the need for economic screening tools, and in a bid to gain more knowledge about the plausibility of motor imagery training in a BRI environment as a backdoor to the motor system, we focused on two research questions. First, we aimed to determine how the abilities for motor imagery and motor execution are connected and how they interact with the ability to control a BRI. Second, we wished to ascertain which cortical networks during resting state would be able to predict the abilities of motor imagery and motor execution with high specificity. We therefore developed a battery of behavioral indicators for the two latent abilities and studied their relationship to resting state networks.

Latent abilities

In many movements, planning, preparation, execution and control go hand in hand, albeit at different degrees. Performance in a motor task recruits several distinct latent abilities. This interplay of latent abilities cannot be measured directly. The use of principal component analysis (PCA) of behavioral indicators, which does not rely on a priori structural assumptions, is a common approach in such cases to unravel this relationship. In PCA, matrix rotation transforms behavioral data into orthogonal, i.e. de-correlated main components. Our hypothesis was that we would detect two main components, one related to motor imagery and the other to motor execution. To validate whether these two components could be understood as orthogonal, we performed several statistical analysis methods, e.g. Horn's parallel analysis and the opaque factor analysis using promax rotation.

Additionally, we expected that BRI would share loadings with both components, indicating that it could bridge motor imagery and execution. In addition to the performance in the brain–robot interface (BRI) task, we therefore applied two behavioral measures to cover imagery and execution of movements. We used the Kinesthetic and Visual Imagery Questionnaire (KVIQ) as an indicator for motor imagery (Malouin et al., 2007), since it uses small movements of individual limbs. Two motor tasks were used as an indicator for motor execution. One was based on fine, visually guided movements, while the other used a task based on control of electromyographic activity.

Network analysis

The power in the α -range (8–14 Hz) over sensorimotor areas during resting state has been proposed as a predictor for the ability to control a brain–robot interface (Blankertz et al., 2010). We recently showed that lateralization of centro-parietal connectivity in the α -range (Vukelić et al., 2014) increases during a brain–robot-interface task. Several measures of connectivity in resting state have been proposed to predict motor learning (Albert et al., 2009; Wu et al., 2014), task performance (Lee et al., 2011; Zhou et al., 2012) or personality traits (Langer et al., 2012; Putman, 2011). We used the phase slope index (PSI), because PSI is very robust against noise (Nolte et al., 2010) and because it requires no prior assumptions about the structure of interaction. PSI indicates the temporal coupling of two signals and the direction of this information flow. Transmission is characterized by a systematic time lag of the two signals, which can be estimated by measuring the increase of a phase-lag over increasing frequencies, and which finally results in a positive phase slope. The sign of the PSI is therefore an indicator of the direction of signal transmission.

Methods

Subjects

We recruited 23 right-handed healthy subjects with a score equal to or above 75 in the Edinburgh Handedness Inventory. The participants

had no habitual drug or alcohol consumption, cognitive or psychiatric impairments, neurological disorders, metal implants or pregnancy. Three subjects were excluded because they did not complete the protocol or because no artifact-free EEG signal could be obtained, resulting in a total of 20 right-handed subjects in the analysis (mean age = 28.5 years, SD = 10.5, range 20–58, 11 female). Subjects were not compensated for their participation and gave their written, informed consent beforehand. The study protocol was approved by the local ethics committee.

EEG & EMG recording

In all experiments, EEG was recorded from 31 Channels (FP1, FP2, F3, FZ, F4, FC5, FC3, FC1, FC2, FC4, FC6, C5, C3, C1, CZ, C2, C4, C6, CP5, CP3, CP1, CPZ, CP2, CP4, CP6, P3, PZ, P4, O1, O2) grounded to AFz and referenced to the right mastoid (TP10). Electromyographic (EMG) activity was recorded from the abductor pollicis brevis and first dorsal interosseus muscles of the left hand in a muscle–tendon montage, and from the flexor digitorum superficialis and extensor digitorum communis muscles of the left forearm in a bipolar montage. All measurements were performed at a sampling rate of 1000 Hz and DC correction with a time-constant of 10 s, using Brain Products Amplifiers and transmitted online to BCI2000 (Schalk et al., 2004) for storage and/or online processing. Data analysis was performed offline with custom written or adapted scripts in MatLab.

Control of a brain robotic interface

The ability to control a BRI was assessed in a task based on closed-loop haptic feedback of kinesthetic imagery of opening the left hand. The task consisted of three runs of 5 min each in length. Each run was separated into 20 trials (60 trials in total). Every trial consisted of three phases (2 s preparation, 6 s kinesthetic motor imagery of opening the left hand, 6 s relaxation) and the onset of each phase was indicated by an auditory cue. Every 40 ms, frequency power in the β -range (16–22 Hz) over sensorimotor areas contralateral to the left hand (FC4, C4, and CP4) was estimated online for a window of 500 ms using an autoregressive model based on the Burg Algorithm with a model order of 32. Our linear classifier detected a decrease in β -power relative to the power during the last 15 s of the other phases (rest & preparation). Desynchronization in the motor imagery phase resulted in the fingers of the left hand being extended by the hand robot (Amadeo, Tyromotion, Austria). When the classifier detected a discontinuation of desynchronization, the finger extension ceased. After the motor imagery phase, the hand was returned to the starting position independently of the subject's brain state. The subjects were instructed to perform kinesthetic motor imagery of hand opening during the motor imagery phase, and to rest during the other phases. We calculated the average of true positive rate and true negative rate (i.e. classification accuracy) as an indicator of motor imagery-based neurofeedback performance (BRI).

Assessment of kinesthetic and visual imagery

Different questionnaires for the assessment of motor imagery vividness, such as the Vividness of Movement Imagery Questionnaire (VMIQ) (Isaac et al., 1986) or the Kinesthetic and Visual Imagery Questionnaire (KVIQ) are available. While VMIQ is based on whole-body movements, KVIQ uses smaller movements of individual limbs, which is more akin to the other behavioral indicators we employed. We used the KVIQ to assess the ability to imagine movements, which was translated in-house into German. The KVIQ consists of 18 concepts of axial, upper and lower limb movements. We assessed the 9 axial and upper limb items, adhering to the described protocol (Malouin et al., 2007) that any movement is first presented to the subject by the interviewer before being executed by the subject and then imagined.

Kinesthetic imagination was assessed with the instruction to imagine feeling the movement from a first-person perspective, and visual imagination was assessed with the instruction to imagine seeing the movement from a third-person perspective. Assessment was performed for both the motor dominant and non-dominant sides. Due to our study focus, only the scores for the non-dominant, i.e. the left upper limbs, were included in our analysis. This resulted in scores for kinesthetic imagery scale (KIS) and visual imagery scale (VIS) of the left side upper-limb movements.

Visuomotor integration

We used an orthotic hand robot (Amadeo, Tyromotion GmbH, Austria) to measure the force applied by the subject with each finger (excluding the thumb) during a fine push and pull task. The force applied by the subject was used to control the position of a ball on a screen in front of the subject. At the same time, a horizontal bar, which was displayed on the screen, moved continuously up and down in a sinusoidal manner at 0.1 Hz. Subjects were instructed to match the position of the ball with that of the horizontal bar by the force they applied to the orthosis for 150 s. We calculated Pearson's correlation coefficient between the time course of the bar and the time course of the average applied force and used the inverse hyperbolic of this coefficient, i.e. its Fisher z-transformation, as an indicator of the subject's ability to perform fine motor movements on the basis of visuomotor integration (VMI).

Tonic contraction

This task was also based on active muscle contraction. The subjects were requested to maintain a target level of muscular activity in each of the four distinct EMG muscles (abductor pollicis brevis, flexor pollicis brevis, flexor digitorum superficialis and extensor digitorum communis). The contraction of each of the four muscles was calculated every 40 ms as the number of zero crossings in the last 500 ms (Airaksinen et al., 2001; Inbar et al., 1986). Before commencing the task the contraction levels at rest and at maximum contraction were measured. During the task, a gray box was shown on the screen at a specific height. The height of the box indicated the target level of muscle contraction, relative to the difference of activity between rest and maximum contraction. The borders of the box indicated the tolerance of the target, defined as 5% of the individual range. In addition, a ball moved up or down, reflecting the level of muscle contraction. It was red while outside the box and green whenever the target contraction level was achieved or maintained. The task consisted of 6 trials for each of the four muscles. The order of the target levels was permuted for each muscle. The subject was allocated 10 s in which to achieve and maintain the target level, with a break of 5 s between the trials. The average time during which the muscular activity remained within the target range was used as an indicator of muscle output control (MOC).

Resting state analysis

Subjects were instructed to sit upright in a relaxed and comfortable position in a chair with their eyes closed. Resting state EEG was recorded for 5 min. We filtered the resting state EEG with a lowpass filter of 45 Hz using a zero-phase lag FIR filter (first order) followed by a spatial Laplacian filter, and cut the signal into epochs of 4 s length. We automatically rejected epochs containing artifacts with an amplitude > 100 μ V and estimated the power spectrum from 1 to 35 Hz over C3 and C4 on the remaining concatenated epochs with Welch's method. We then fitted a 9-parameter-model (Blankertz et al., 2010), which separates the power spectrum into a noise floor and two peaks on the log power spectrums of C3 and C4. The average of the maximum elevation over the noise floor level at both electrodes, which has been proposed as

predictor of BRI (Blankertz et al., 2010), was used as the gold standard control of our predictor (gold standard predictor, GSP).

We filtered the resting state EEG accumulated for the estimation of sensorimotor power with a band-pass filter between 6 and 16 Hz using a zero-phase lag FIR filter (first order). We performed two steps of artifact removal. In the first step, we cut the signal into epochs of 4 s length and automatically rejected epochs containing artifacts with an amplitude > 60 μ V. In the second step, we performed an independent component analysis (Hyvarinen, 1999), identified components with remaining artifacts by visual inspection and removed them from the signal. Finally, we filtered the signal with a spline interpolation spatial Laplacian (Oostenveld et al., 2011). On the basis of this artifact-free signal with increased spatial resolution, we calculated in a second step for non-overlapping epochs of 4 s length the phase slope index (Ψ and Ψ_{net}) for the frequency range from 8 to 14 Hz based on a segment size of 1 s length. In the original version of this calculation, Ψ is calculated as the average across epochs (Nolte et al., 2008). While the sign of Ψ or Ψ_{net} indicates whether the channel is a transmitter (positive sign) or a receiver (negative sign) in that epoch, the magnitude can be influenced by the power. We chose an approach slightly different from the original authors' approach by taking the average of the sign. After cutting the continuous resting state into epochs, averaging the sign of Ψ or Ψ_{net} across the epochs results therefore in a robust estimation of the likelihood of the direction and stability of a connection between two channels. In this vein, the likelihood that a connection between two channels i and j across epoch e is transmitting or receiving was calculated based on the single epoch estimates of Ψ :

$$\Psi_{ij}(e) = \mathcal{J} \left(\sum_{f \in F} C_{ij}^*(f, e) C_{ij}(f + \delta f, e) \right)$$

$$L\Psi_{ij}(f) = \frac{\sum_{e=1}^E \text{sgn}(\Psi_{ij}(e))}{E}$$

In the same way, we calculated how often channel i was a net transmitter or receiver as the mean of the sign of Ψ or Ψ_{net} across epoch e and receiving channel j

$$L\Psi_{\text{net}}(i) = \frac{\sum_{e=1}^E \text{sgn} \left(\sum_j (\Psi_{ij}(i, e)) \right)}{E}$$

Statistical analysis

A Kolmogorov–Smirnov-test was used to test all behavioral indicators (KIS, VIS, VMI, MOC), the ability for BRI-control and the resting state predictors (GSP, $L\Psi$ and $L\Psi_{\text{net}}$) for normal distribution. We also performed a t-test across subjects for each channel or connection ($L\Psi$ and $L\Psi_{\text{net}}$) to test the likelihood of it being a transmitter or receiver. We finally z-scored the values of the behavioral indicators.

To estimate the number of components necessary to explain the data, we used Kaiser's eigenvalue criterion, Horn's parallel analysis (Horn, 1965) and performed a visual inspection of the Scree-plot. We additionally performed a visual inspection of the correlation matrix, and a factor analysis with iterative promax rotation. This rotation aims to reduce the number of necessary factors by allowing factors to correlate. If factors were still uncorrelated after opaque rotation, we took this as evidence that PCA would be warranted to assess the latent abilities. For the analysis of the dimensional structure, we finally performed a PCA.

We performed a bootstrap analysis to assess the loadings of the BRI-task with the two main components. Specifically, we replaced BRI with random white noise, kept the other variables fixed, and performed a PCA. We repeated this replacement 10,000 times and counted how often white noise resulted in loadings higher than or equal to BRI with

the two main components. As white noise has expected loadings of zero, this allowed us to estimate the statistical significance of finding variables sharing loadings with both main components of the same magnitude as BRI, i.e. recruiting the abilities for motor imagery and motor execution.

For prediction analysis, we calculated Pearson's correlation between subject's main component scores and their resting state network measures. All statistical analyses were performed with an assumed significance level of 0.05; we used Benjamini and Hochberg's false discovery approach to limit the multiple-comparison error during the network analysis (Benjamini and Hochberg, 1995). To explore the specificity of prediction, we selected the two connections, which had the highest correlation to each component.

Results

Characterization of the behavioral assessments

Subjects had significantly lower scores in KIS than in VIS ($\Delta = 0.783$, $p < 0.001$, t-test) when assessed with the KVIQ. Nonetheless, both subscores correlated strongly with each other ($r = 0.80$, $p < 0.001$). Cronbach's α was high for both scores (KIS $\alpha = 0.896$, VIS $\alpha = 0.733$). Symmetry between the dominant and non-dominant upper limbs was pronounced ($r = 0.879$, $p < 0.001$). These results replicated the results described by the original authors for the complete KVIQ (Malouin et al., 2007; Randhawa et al., 2010). In the VMI task, subjects were usually able to follow the sinusoidal, but revealed the highest performance variation at the turning points (see Fig. 1A). In the MOC task, the average probability of being in the target zone was approximately 5% immediately after onset of the trial, which is equivalent to chance level. In the course of the task, probability increased, reaching a plateau of approximately 60% about 3 s after trial onset (see Fig. 1B). The BRI task was characterized by initially low classification accuracy at chance level, which increased as the trial progressed, reaching a plateau after the first second (see Fig. 1C).

Characterization of cortical network activity during resting state

During resting state, the overall pattern was characterized by bihemispheric lateral parietal transmission, midline postcentral receiving and bihemispheric dorsal precentral transmission. Global network activity at both hemispheres correlated significantly ($r = 0.838$, $p < 0.001$), indicating symmetry between the left and right hemispheres (see Fig. 2). The two indicators for motor imagery (KIS, VIS) were characterized by transmission in the bilateral posterior parietal and left premotor areas, with midline and right frontal receiving, while the two behavioral indicators for motor execution (VMI, MOC) were characterized by transmission from the left to right motor areas (see Fig. 3).

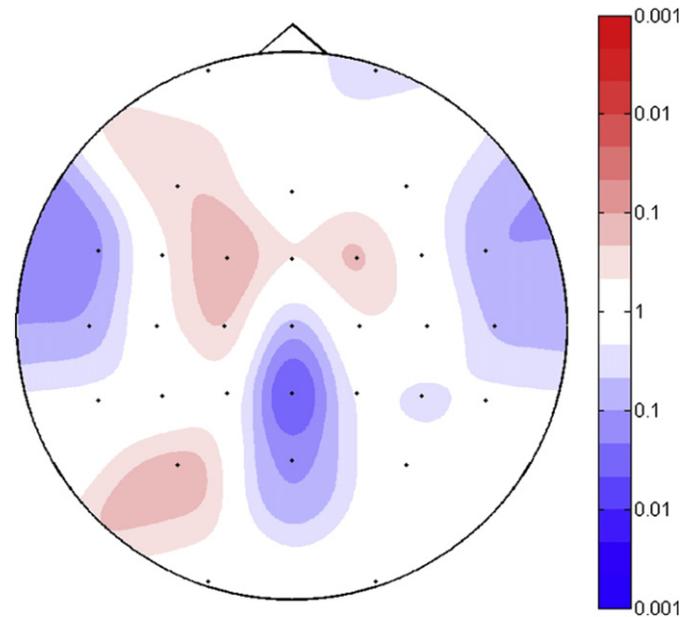


Fig. 2. Resting state network activity: The figure shows the EEG network activity during resting state. For $L\psi_{net}$ saturation of the colors indicates the significance level of the t-test on a log10 scale. Red colors indicate a positive mean and blue colors a negative mean. We found no significant connections based on $L\psi$ after limiting the false discovery rate to 5%.

Characterization of latent abilities for motor imagery and motor execution

The visual inspection of the correlation matrix shows two distinct clusters (see Fig. 4A). This finding is replicated by the oblique factor analysis, disclosing two factors with a distinct loading profile (see Fig. 4B), strikingly similar to the one achieved by orthogonal PCA (see Fig. 5A). Pearson's correlation between the latent factors was not significant ($p = 0.58$) and limited to 0.13 (see Fig. 4C). When inspecting the Scree-plot, Horn's parallel analysis and Kaiser's eigenvalue > 1 criterion (2.07, 1.48, 0.84, 0.41 and 0.19), two main components were apparent (see Fig. 4D).

The inspection of the component coefficients for the PCA allows the following characterization (see Fig. 5A). The first component had a high loading on visual and kinesthetic imagery (0.62 and 0.64), while the second component had a high loading on tonic contraction and visuomotor integration (0.52 and 0.72). Both components had medium loadings on the ability to control the BRI (0.45 and 0.37). According to our bootstrap analysis, loadings of such magnitude with the two components are very unlikely ($p = 0.005$). The two main components

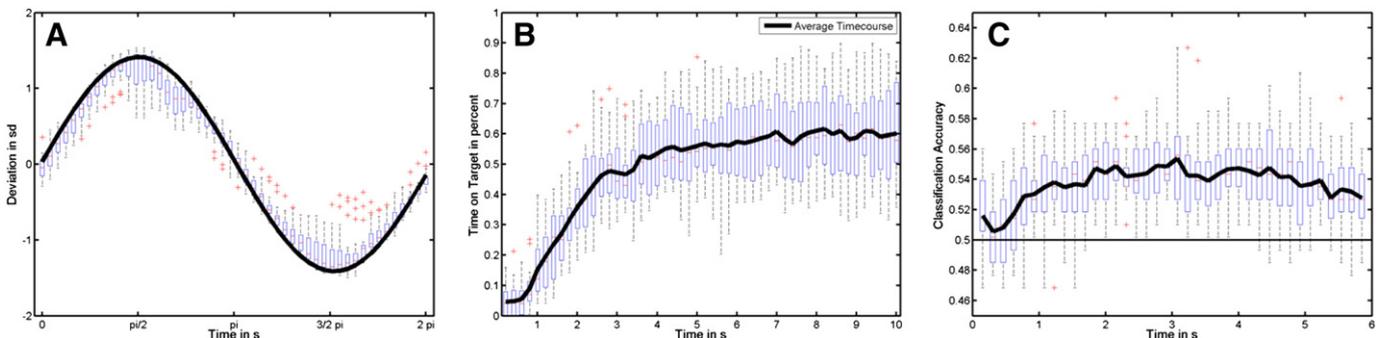


Fig. 1. Characterization of motor execution tasks: In all figures, box plots visualize the distribution of performance across subjects. A. Characterization of the visuomotor integration task indicated as z-scored force deviation and averaged over all 15 repetitions of the sinusoidal movement. Black trace indicates the expected perfect sinusoidal. B. Characterization of tonic contraction task, indicated as time on target (1.0 = 100%). Black trace indicates the grand average across all subjects. C. Characterization of the brain-robot interface task, indicated as classification accuracy averaged across all 60 runs. Black trace indicates the grand average across all subjects.

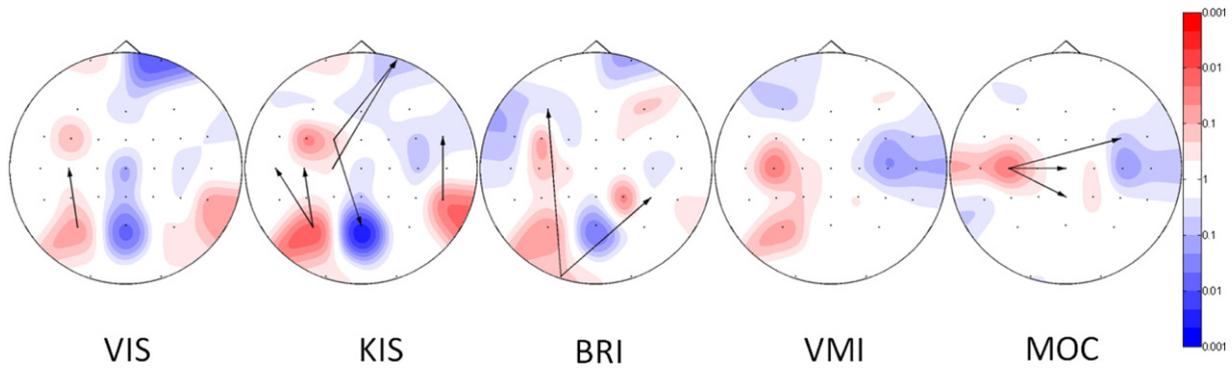


Fig. 3. Relationship of resting state network activity to performance: The figure shows the correlation of EEG network activity during resting state with performance in the five tasks. For $L\Psi_{net}$ saturation of the colors indicates the significance level of Pearson's correlation on a log 10 scale. Red colors indicate a positive mean and blue colors a negative mean. As $L\Psi$ is asymmetric we are only depicting positive significant correlations with arrows in the direction of transmission, with the false discovery rate limited to 5%.

therefore plausibly reflect two distinct abilities of motor imagery and motor execution, with BRI reflecting both abilities (see Fig. 5A).

Prediction of latent abilities of motor imagery and motor execution

The network topographies disclosed by the latent abilities of motor imagery and execution are very similar to those observed for the

respective indicators. More specifically, the ability of motor imagery was characterized by left-lateralized transmission from the parietal to sensorimotor areas and from the sensorimotor to contralateral motor and frontal areas (see Fig. 5B). The connections showing the highest correlation with motor imagery transmitted signals from P3 to C3 ($r = 0.78, p < 0.001$) and from C1 to FP2 ($r = 0.78, p < 0.001$). The ability of motor execution was characterized by connectivity within the left

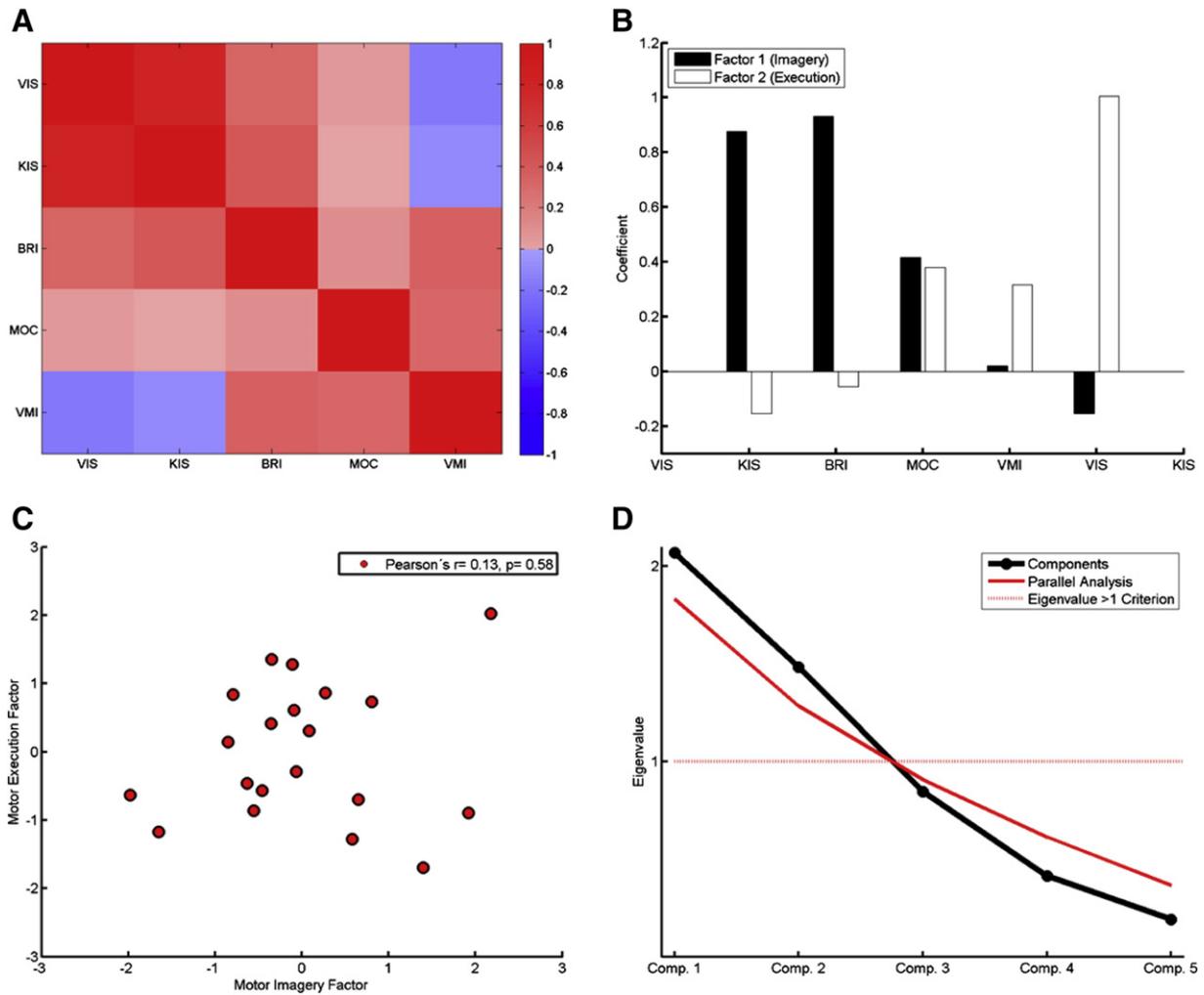


Fig. 4. Results of the dimensionality analysis: A. Correlation coefficients for the visual and the kinesthetic imagery scale (VIS & KIS), performance in the brain-robotic-interface (BRI), the tonic contraction task (MOC) and the visuomotor integration (VMI) task. B. Loadings of the different indicators based on oblique factor analysis with promax rotation. C. Scatter plot of the oblique factor scores and their respective Pearson's correlation coefficient. D. Scree-plot of the eigenvalues of the principal component analysis and Horn's parallel analysis indicating two main components.

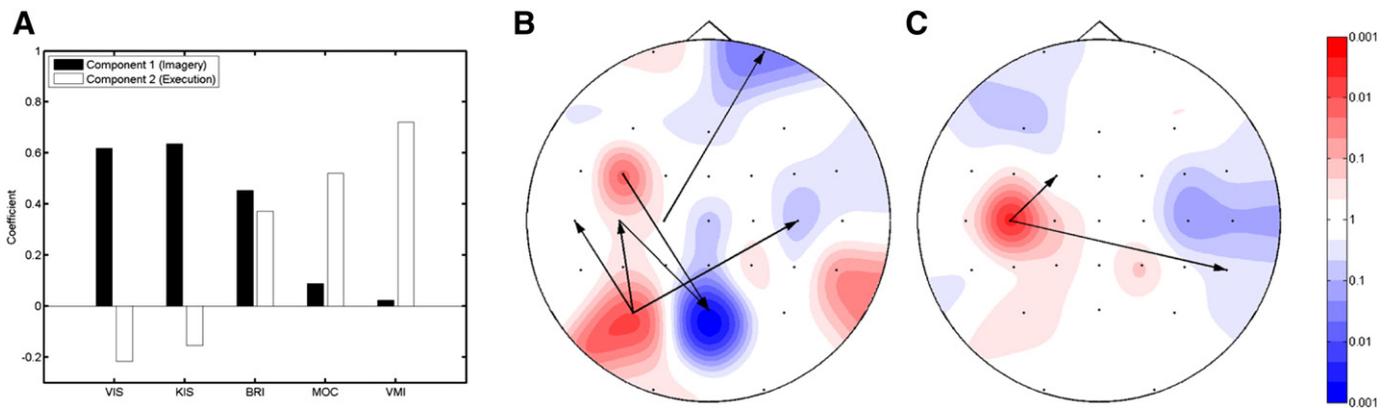


Fig. 5. Results of the principal component analysis: A. Component coefficients for the visual and the kinesthetic imagery scale (VIS & KIS), performance in the brain-robotic-interface (BRI), the tonic contraction task (MOC) and the task based on visuomotor integration (VMI). B. Shows the log 10 of p-values of Pearson's correlation of the score in the first component (motor imagery ability). For $L\Psi_{net}$, red colors indicate a positive correlation and blue colors a negative correlation. As $L\Psi$ is asymmetric we are only depicting positive significant correlations with arrows in the direction of transmission, with the false discovery rate limited to 5%. C. Showing the same plot as C for the second component (motor execution ability).

and right motor regions (see Fig. 5C). The connections showing the highest correlation with motor execution transmitted signals from C3 to CP6 ($r = 0.64$, $p = 0.002$) and from C3 to FC1 ($r = 0.63$, $p = 0.003$). When these four connections were used to predict the abilities, they had a specificity of 86% and a sensitivity of 50% for the motor imagery ability, and a specificity of 95% and sensitivity of 74% for the motor execution ability. In summary, they predicted 68% of the motor imagery ability and 84% of the motor execution ability.

The gold standard predictor showed a significant correlation with the ability to control the BRI ($r = 0.61$, $p = 0.004$), similar in magnitude to results published elsewhere (Blankertz et al., 2010). In general, we observed a lower correlation of the GSP with the latent abilities, which was higher with the ability of motor imagery ($r = 0.46$, $p = 0.04$) than with motor execution ($r = 0.39$, $p = 0.09$). For the motor imagery ability, the specificity of the GSP was 85%, while its sensitivity was 21%. For the motor execution ability, the specificity of the GSP was 79%, while its sensitivity was 15%. In conclusion, the GSP was able to predict 21% of the motor imagery ability and 15% of the motor execution ability.

Discussion

We show that the ability to control a BRI is connected to the abilities of motor imagery and motor execution. These respective abilities are orthogonal in the sense of being uncorrelated. Additionally, they are recruiting distinct networks, which can be estimated by a short resting state EEG session. Effective connectivity measures can predict the two latent abilities with slightly higher specificity and relevantly better sensitivity than the current gold standard predictor.

Network topography

Electrophysiological studies focusing on the power domain have shown very similar patterns of event-related desynchronization for both imagery and execution of hand movements (Decety, 1996; Ehrsson et al., 2003; Gao et al., 2011; Jeannerod, 1995; Kaiser et al., 2011; Miller et al., 2010). Power during resting state has also been shown to be a reliable predictor of the ability to control a BRI (Blankertz et al., 2010). We extend this observation by demonstrating how imagery and execution of the left hand movements are characterized by topographically different cortical networks. We show that the ability to plan and inhibit planned movements, i.e. to perform motor imagery, is linked to a network between the left parietal and motor areas as well as to a further network between the left motor and right frontal areas. These networks are in accordance with our knowledge about networks involved in movement planning (Creem-Regehr, 2009; Haller et al., 2009; Johnson-Frey et al., 2004; Lewis, 2006;

Rushworth et al., 2003), while movement inhibition has been linked to the right prefrontal cortex (Chikazoe, 2010; Levy and Wagner, 2011; Swann et al., 2009; Wager et al., 2005). The ability to execute movements of the left hand is characterized by connectivity within bilateral motor regions, especially by transmission from the left to right motor areas. This might reflect the relay of planned movements from the left to the right hemisphere, in agreement with hemispheric specialization in right-handers (van den Berg et al., 2011), bilateral integration (Grefkes et al., 2008; Horenstein et al., 2009) and a final common pathway originating from the primary motor cortex contralateral to the executed hand movement (Chouinard and Paus, 2006).

Screening utility

We have demonstrated that it is possible to predict the abilities of motor imagery and motor execution with network analysis measures of resting state oscillatory activity. Our data acquisition paradigm for determining effective brain connectivity is short (5 min), comfortable (in resting state with eyes closed), and economic (light-weighted EEG setup). An easily applicable physiological network marker is highly desirable, particularly for evaluating stroke survivors who often suffer from impairments of motor imagery and execution to different degrees (de Vries et al., 2011; Wiese et al., 2005). Since no direct and objective behavioral correlates of motor imagery are available as yet, the technique presented here might be particularly helpful for estimating the ability of motor imagery. Network analyses of resting state measurements may therefore provide the basis for a screening tool to determine the suitability of neurological patients for motor-imagery based rehabilitation.

Implications for the interplay between motor imagery and execution

Extending this line of research, we have shown that a brain-robot interface that is providing haptic/proprioceptive feedback is a suitable backdoor to the motor system, i.e. offers a way to recruit the abilities for both motor imagery and execution as well as their corresponding cortical networks. We conclude this based on the following line of arguments. The correlation matrix indicated two clusters (see Fig. 4A). In this vein, the oblique factor rotation did not result in correlated factors (see Fig. 4C). Furthermore, Kaiser's eigenvalue criterion, the Scree-plot and Horn's parallel analysis suggest two main components as well (see Fig. 4D). These findings provide converging evidence of a latent two-dimensional structure. Second, these two components exhibited distinct loadings for the performance in the motor imagery and motor execution tasks (see Fig. 5A). Moreover, the cortical networks connected with the latent abilities can be interpreted as networks involved in

imagination (parieto-central, see Fig. 5B) and execution (interhemispheric, see Fig. 5B). Finally, the bootstrap analysis indicated that the loadings that the BRI task shares with these two orthogonal components are highly significant. Together, these findings suggest that the BRI task recruits both motor imagery and motor execution abilities and offers thereby a way to bridge the gap between these two networks.

We want to stress that this does not imply that the abilities for motor imagery and more execution are completely unrelated. In fact, other authors have already argued that motor imagery is essential for proper sequencing of a motor execution program and that this aspect could even be improved by appropriate training (Page et al., 2011; Schack et al., 2014). We suggest that our findings can also be interpreted along these lines as evidence that the specific interaction of imagery and execution is important for the final motor performance. We base this conclusion on the observation that in all tasks of our study, the two abilities were mixed to varying degrees (see Fig. 5A). Additionally, the spatial topography of the networks (see Figs. 5B/C) might be considered as circumstantial evidence for a sequential processing, i.e. a motor schema has first to be imagined (parieto-central activation) before it can be executed (interhemispheric activation). In this framework, we find it very intriguing that BRI exhibited high positive loadings on both abilities. The conclusion we therefore draw is that, if the ability for motor imagery is still intact, while the ability for motor execution is impaired, a BRI might present a backdoor to the execution part of the motor system.

However, the only striking difference between the BRI approach we used and pure motor imagery tasks is the passive movement of the imagined hand executed by the hand robot. This raises the question why this should result in a shared loading of BRI to motor imagination and execution. In this context, Szameitat and colleagues have already shown that – in healthy subjects – the pattern of neural activation in overt execution was best resembled by passive movement, while – for stroke survivors – attempted overt execution was best resembled by motor imagery (Szameitat et al., 2012). It is known that passive movements result in evoked potentials over the primary motor cortex, implying the involvement of the motor execution system during proprioception (Seiss et al., 2002). Moreover, muscle spindles are the main proprioceptors (Proskes and Gandevia, 2009) and, being actively fine-tuned by the central nervous system to predict future sensory states, have been shown to work on the basis of forward sensory models (Dimitriou and Edin, 2010). This predictive function has been linked to efference copies originating from primary motor regions. A mismatch between prediction and proprioception has therefore been shown to modulate the connectivity between the primary motor and somatosensory cortices (Gandolla et al., 2014). We argue here that our findings provide further evidence that proprioception is not a passive, but an active sense closely linked to motor execution. The use of a brain–robot-interface linking motor imagery with passive movement might thus activate this forward sensory part of the motor system, and might thereby establish the shared loading with motor execution.

Clinical implications

So far, studies in stroke rehabilitation based on motor imagery training alone without haptic/proprioceptive feedback have been inconclusive (Braun et al., 2013; Ietswaert et al., 2011; Page et al., 2011). Our results suggest that this could potentially be explained by the different cortical networks recruited by the abilities for motor imagery and motor execution. Moreover, disentangling different intrinsic networks for motor imagery and motor execution may facilitate tailored approaches. Network modulations could include training with on-line feedback (Krusienski et al., 2012; Wei et al., 2007) or with neurostimulation techniques (Arai et al., 2011; Chen et al., 2003; Lu et al., 2012; Plewnia et al., 2008; Polanía et al., 2011, 2012a, 2012b). However, it should be noted that, in neurological conditions such as stroke, lesions and subsequent functional reorganization might result

in cortical networks with a different topography than those observed in healthy subjects (Grefkes and Fink, 2011; Hamzei et al., 2006; Lefebvre et al., 2012; Szameitat et al., 2012; Wang et al., 2010). Simply trying to reinstate networks similar to those observed in healthy subjects might therefore not be sufficient to induce functional recovery. Instead, backdoors to the motor system are important, i.e. methods to recruit networks important for motor execution, even without overt execution.

Conclusion

In summary, the results presented here pave the way for a number of different future research approaches. We have demonstrated that resting state EEG can be used for screening subjects for latent abilities of motor imagery and motor execution. We have also shown that, although motor imagery and execution recruit different cortical networks, brain–robot-interfaces are able to activate both of them. Moreover, the approach presented here can support the development of interventions that aim specifically to improve motor execution and imagery by modulation of cortical networks (for example, by brain stimulation), thereby leading to novel methods of motor rehabilitation training.

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