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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.

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, FCZ, 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.