A Brain-Robot Interface for Studying Motor Learning after Stroke

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Abstract-Despite intensive efforts, no significant benefit of rehabilitation robotics in post-stroke motor-recovery has yet been demonstrated in large-scale clinical trials. The present work is based on the premise that future advances in rehabilitation robotics require an enhanced understanding of the neural processes involved in motor learning after stroke. We present a system that combines a Barret WAMTM seven degreeof-freedom robot arm with neurophysiological recordings for the purpose of studying post-stroke motor learning. We used this system to conduct a pilot study on motor learning during reaching movements with two stroke patients. Preliminary results indicate that pre-trial brain activity in ipsilesional sensorimotor areas may be a neural correlate of the current state of motor learning. These results are discussed in terms of their relevance for future rehabilitation strategies that combine rehabilitation robotics with real-time analyses of neurophysiological recordings.

I. INTRODUCTION

In 2011, about 795,000 people in the United States experienced a stroke [1]. It is one of the leading causes of adult disabilities, with about 80% of patients being affected by motor impairment [2]. Even after six months of intense rehabilitation efforts about 50% of patients still show motor impairments [3]. To improve their quality of life, and reduce dependency on others, novel rehabilitation strategies need to be explored.

Multiple approaches exist to improve rehabilitation: Bilateral training [4], constraint-induced movement therapy (CIMT) [5], EMG biofeedback [6], electrostimulation [7], and mental practice [8]. In recent years, several robotic systems for stroke-rehabilitation have been presented, including MIT-Manus [9], ARM Guide [10], MIME [11], ARMin II [12], Lokomat [13, 14], Hocoma [15], and Bi-Manu-Track [16]. Although using robotics in stroke neurorehabilitation allows standardized and individually tailored training protocols, this form of therapy seems not to be superior to conventional manual high-intensity physical therapy [17].

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Fig. 1: Subject wearing an EEG-cap while being attached to the seven DoF Barrett WAM arm.

The present work is based on the premise that future advances in rehabilitation robotics require an enhanced understanding of the neural correlates of motor learning. Identifying such correlates may yield helpful insight into processes of brain plasticity during therapy, which could be used to evaluate a therapy's success and adapt current rehabilitation strategies. In particular, the combination of rehabilitation robotics with brain-computer interfaces (BCIs) may facilitate a real-time adaptation of the robotic system to the patient's needs, e.g., by optimizing factors such as task-difficulty [18–20].

In the present paper, we describe a novel system developed for this purpose. The system combines a seven degree-offreedom (DoF) robot arm with an EEG-based BCI-system (cf. Figure 1). We present results of a pilot study, in which we used this system to study the neurophysiological correlates of motor learning during reaching movements in two stroke patients. Initial results suggest that pre-trial bandpower in contralesional sensorimotor areas may be a neural correlate of motor learning.

The structure of this paper is as follows. We provide a detailed description of the system in Section II, and present the pilot study in Section III. We conclude this paper by discussing the relevance of our results for future rehabilitation strategies that combine rehabilitation robotics with real-time analyses of neurophysiological recordings.

II. BRAIN-ROBOT INTERFACE SETUP

The following section describes a system developed to understand and support rehabilitation processes after stroke by combining rehabilitation robotics with real-time analysis of neurophysiological recordings. The system (Figure 2) consists of:

- (i) A seven DoF Barrett WAMTM robot arm: The mounting position of the seven DoF robot arm, resembling that of a human arm (cf. Figure 1), enables a broad range of movement tasks.
- (ii) An attachment to connect the human arm to the robot: The attachment consists of two parts attached to the subject's lower arm, which results in a direct transmission of force from the subject's arm to the robot and vice versa (cf. Figure 1). The attachment incorporates a magnetic link, which releases the subject in case of a movement beyond the subject's body constraints or in case movements are too rapid. In order to increase comfort while still maintaining data accuracy, the subject's arm rests on cellular rubber and is fixed in position with VelcroTM.
- (iii) A real-time EEG system: We use an actiCAP electrode cap with up to 128 electrodes in combination with a QuickAmp amplifier (Brain Products, Gilching, Germany) for this system. The signals are acquired from the amplifier using BCI2000 [21] and processed in realtime by the additional module BCPy2000 [22]. The information extracted from the neural signals can then be used to control the robot, e.g., for giving haptic feedback to the patient, or to adapt study parameters such as task difficulty in real-time.
- (iv) Visual and auditory feedback: While sensorimotor feedback is a critical component for motor learning, several studies have demonstrated the additional value of visual or auditory feedback [23–25]. For this reason, the system was further equipped with the capability to provide visual and auditory feedback in a continuous manner.

The robot can (directly) interact in several ways with the patient:

Passive: The system can be used to accurately track the position and velocity of the human arm during a task (cf. Section III), allowing synchronized analysis of neural signals and the state of the subject's arm. The robot uses gravity compensation to avoid burdening the subject with its own weight.

Supportive: Severely affected stroke patients often struggle with compensating gravity during movement of their arm. The robot can be used to compensate gravity for its own weight as well as for the weight of the subject's arm, facilitating movement. Furthermore, the robot can help the subject to follow a certain trajectory, e.g., if the subject's arm drifts away, the robot can gently lead it back to the desired trajectory.

Interfering: The robot arm can be used to perturb the subjects' movements, e.g., by force fields. This interference



Fig. 2: Visualisation of the components of the system.

can be dynamically modulated by the subject's current stateof-mind, as measured by the real-time EEG system.

Autonomous: The robot can be used to apply external movements to the human arm, while the system enables us to simultaneously analyse their neural correlates.

Depending on information extracted from the neural signals, these modes can be dynamically adapted to the subject's current mental state.

In contrast to most other applications of robotics in stroke therapy, our system enables studying the neural correlates of motor learning after stroke. The interaction of the parts of our system opens up a number of possibilities, which are discussed further in Section IV.

III. NEURAL CORRELATES OF MOTOR LEARNING IN STROKE

In this section, we present preliminary results on neural correlates of motor learning in stroke, based on experimental EEG data from two patients. We first describe the subjects, the study design, the recorded data, and the data analysis procedure. We then present empirical evidence that in the two stroke patients pre-trial power of the EEG in the μ (8–14 Hz) and β -ranges (20–45 Hz), originating primarily in sensorimotor areas, predicts the time-to-target of 3D reaching movements on a trial-to-trial basis.

A. Subjects

Two stroke patients and six heathy control subjects participated in the present study. All controls (3 male, 3 female), recruited from the local student body (mean age 29.5 ± 4.5), were right-handed and thus conducted the experiment with their right arm. One stroke patient (AO - female, 27 years old) had suffered a left-hemispheric stroke with a right-sided hemiparesis, aphasia and right-sided hemianopsia eleven years previously. In spite of extensive rehabilitation, she retained significant motor impairment of her right arm, which she used in this study to perform the reaching movements. The other patient (GS - male, 73 years old) had suffered a left-hemispheric stroke four years previously, with rightsided hemiparesis and aphasia. Lysis reduced the rightsided hemiparesis but led to left cerebellar bleeding resulting in left-sided hemiataxia and dysarthrophonia. Therefore he performed the reaching movements with his left arm. Proprioceptive feedback was intact in both patients.



Fig. 3: Different phases of visual feedback shown to the subject. The blue ball represents the current position of the endeffector. The bar at the top of the screen, as well as the poles of the balls, provide information on the depth of the balls. (a) The yellow ball represents the target during movement preparation. (b) The target's color switches to green, the subject is instructed to begin the reaching movement. (c) The target was reached, the current target disappears and the initial position appears as new target.

B. Study Design

The subjects were attached with their arm to the robotic system, as shown in Figure 1, and were placed approximately 1.5 meters in front of a computer screen. During each trial, this screen displayed the current position of the robotic arm's end-effector as a blue ball and the target as a yellow or green ball, depending on the current phase (Figure 3). The initial position, in which the arm was hanging beside the body, was chosen independently by each subject. Corresponding to the subject's initial arm position, this position was in the leftor right hand corner of the screen. At the beginning of each trial the subject was told to sit quietly and relax. No balls were shown in this phase. After five seconds, a yellow ball appeared at a randomized location (Figure 3a) and the current position of the end-effector was shown. The subject was instructed to prepare a 3D reaching movement to the position indicated by the yellow ball during this phase. After another 2.5-4 seconds (randomly chosen from a uniform distribution), the yellow ball turned green (Figure 3b), instructing the subject to initiate the reaching movement and bring the blue ball in congruence with the green ball. During actual movement, continuous visual feedback was provided about the end-effector's current position. A reaching movement was considered complete when the subject moved the endeffector within 1.5 cm of the target location, or if the subject exceeded a ten seconds time limit. In either case, the green target ball disappeared and was replaced by a green ball at the initial position of the end-effector (Figure 3c). This prompted the subject to return to their original arm position. When the subject moved the end-effector to within 4 cm of the initial position, the robot arm gently pulled the end-effector to it's precise starting position for the next trial.

Subjects performed blocks of 50 trials. In each trial, a different target location was chosen from a sphere located in front of the subject. In order to determine a range of reachable targets, taking into consideration individual stroke-related impairments, each subject determined the center and radius of the sphere prior to initiation of the first trial by moving their arm to multiple comfortable positions in front of their body. In the current study, subjects chose radii

from 5–9 cm. Stroke patients performed three blocks with brief intermissions of one minute. Healthy control subjects performed four blocks each.

C. Experimental Data

During the reaching movements, a 120-channel EEG was recorded at 1 kHz sampling rate, using active EEG electrodes and a QuickAmp amplifier (BrainProducts, Gilching, Germany). Electrodes were placed according to the 10-20 system, with Cz as the initial reference electrode. All data were re-referenced to common average reference offline.

D. Data Analysis

To track each subject's learning process over the course of the experiment, we computed the time-to-target (TTT) for each trial, i.e. the time required from the instruction to initiate the movement to reaching the target. In order to eliminate variations in TTT due to different target locations, we divided the TTT of each trial by the distance of the target from the initial position of the end-effector. In the six healthy control subjects, we observed a continuous decline in TTT over the course of the experiment, reflecting successful motor-learning processes (Figure 4). Patient AO displayed a similar learning process, although with substantially slower movements (Figure 5). Patient GS also performed substantially slower than healthy controls, but showed only minor signs of successful task-learning (Figure 6). Furthermore, GS showed signs of fatigue after 119 trials, resulting in a stepwise increase in TTT. We thus included only the first 119 trials in the analysis of GS's data.

In the following, we investigate whether TTT is correlated on a trial-to-trial basis to pre-trial EEG, recorded in the five seconds resting-period prior to presentation of the next target. To do so, we high-pass filtered the recorded EEG at 3 Hz, and separated the data into (ideally) statistically independent components (ICs). This was done by first reducing the data to 64 principal components and then running the SOBIalgorithm [26]. We inspected each IC manually and rejected those which were not of cortical origin (cf. [27]). Source localization was performed for every remaining IC, using a standardized head model and electrode locations with minimum-norm estimation [28]. We then computed pre-trial log-bandpower of each non-artifactual IC in three frequency bands (using an FFT in conjunction with a Hanning window): μ (8–14 Hz), low β (20–30 Hz), and high β (30–34 Hz). These frequency bands are known to be related to motor processes [29]. Finally, we correlated pre-trial bandpower of every IC and every frequency band with TTT. Statistical significance of correlation was estimated by a random permutation test with 10.000 iterations [30].

E. Experimental Results

Here, we report experimental results from the two stroke patients only. In patient AO, we found two ICs for which pre-trial bandpower in the μ -range displayed significant negative correlations with TTT. Figure 7 shows the cortical origins of the first IC, located primarily in right sensory cortex. For this IC, we found a correlation of $\rho = -0.27$ between TTT and μ -bandpower (p = 0.009 with Bonferroni correction). The second IC, in which we found a correlation of $\rho = -0.26$ between TTT and μ -bandpower (p = 0.012with Bonferroni correction), displays a clear focus in the primary motor cortex of the right hemisphere. In patient GS, we found one IC that displayed a marginally significant positive correlation of bandpower in the high β -range with TTT ($\rho = +0.24$, p = 0.095 with Bonferroni correction). This IC showed a less clear focus than the ones in patient AO, extending from left occipital cortex to left sensorimotor cortex (Figure 9).

IV. DISCUSSION AND OUTLOOK

Our results indicate that pre-trial EEG in sensorimotor areas may be a neural correlate of motor learning in stroke patients. Obviously, tests with a larger patient population are needed before general conclusions can be drawn. Furthermore, patient GS did not demonstrate successful tasklearning (cf. Figure 6), casting doubt on whether the IC in Figure 9 represents motor-learning processes or neural correlates of motor variation. It is noteworthy, however, that in both patients we found EEG signals in ipsilateral sensorimotor areas to represent the current motor state. This is in congruence with reports from neuroimaging studies that stroke patients utilize the ipsilateral hemisphere for compensating motor deficits [31, 32].

Source localization was performed with a standardized head model and did not take into account the lesion's location, as no MRI scan data was available to us. One has to keep in mind that using a standardized head model might have distorted the source localization results.

In this pilot study we concentrated on analysing frequency bands related to motor processes, but in further studies this focus should be extended to delta and theta bands due to their connection to neuroplasticity.

The novel brain-robot interface presented here combines real-time analysis of neurophysiological recordings with a seven DoF robot arm. In a pilot study, we have demonstrated that the system can be used to study neural correlates of motor-learning after stroke. In the following, we discuss how



Fig. 4: Mean and standard deviation of the changes in timeto-target across the experimental session for the six healthy control subjects.



Fig. 5: Time to target across trials for patient AO.



Fig. 6: Time to target across trials for patient GS.



Fig. 7: First IC of patient AO: Pre-trial μ -power (8–14 Hz) in right sensory cortex correlates with time-to-target ($\rho = -0.27$, p = 0.009).



Fig. 8: Second IC of patient AO: Pre-trial μ -power (8–14 Hz) in right motor cortex correlates with time-to-target ($\rho = -0.26$, p = 0.012).



Fig. 9: Patient GS: Pre-trial β -power (30–45 Hz) in left sensorimotor- and occipital cortex correlates with time-to-target ($\rho = +0.24$, p = 0.095).

the real-time capability of the system, not yet utilized in the experimental work presented here, can be utilized for novel stroke-rehabilitation strategies.

Direct brain-robot control: Based on BCI-technology, the robot could be controlled or influenced by human thought in real-time. First successful studies on this topic have been conducted with stroke patients using only one DoF [33, 34]. In severely impaired patients, this approach may be used to sychronize movement intent with execution by having the robot carry out the movement inferred by the BCI. Preliminary evidence suggests that this may support processes of brain plasticity involved in motor-recovery [18, 35, 36].

Cognitive Monitoring during patient-robot interaction: Cognitive Monitoring detects changes in the ongoing cognitive user state by using standard measures for singletrial EEG analysis or measures resulting from (passive) BCI research (cf. [19]). Changes in cognitive state are valuable information for identifying processes occuring during humanrobot interaction. In particular, such changes can be used to monitor the success of motor-learning and the impact of therapy on the patient. The detectability of different aspects of cognitive user state, like cognitive load [37], perception of errors [38], the perceived loss of control [39], and vigilance [40], has already been shown in general human-machine systems [41], and may find applications in human-robot interaction for stroke rehabilitation. For example, this information could be fed back to the user via neurofeedback to induce mental states beneficial to successful motor learning. In a rehabilitation scenario involving a supportive humanrobot interaction, the degree of support provided by the robot could be adapted to the difficulty currently perceived by the patient. Another example would be the detection of patterns in subjects' behaviour which impair the learning process. If such patterns can be detected reliably with a BCI, the robot arm could support the patient by counteracting the undesired movement patterns. From our perspective, the approach of combining human-robot interaction with BCI

technology is highly promising. In comparison with direct brain-robot control, we do not have to face the problem that the available bitrate of current BCI-system is not sufficient to control multiple degrees of freedom of a robot arm reliably. The task of three dimensional steering of the robot arm can be supported or performed by the robot itself, while being optimized by information about the patient's cognitive state.

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