An EEG-Based Brain-Machine Interface to Control a 7-Degrees of Freedom Exoskeleton for Stroke Rehabilitation

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Abstract Brain machine interfaces (BMIs) have previously been utilized to control rehabilitation robots with promising results. The design and development of more dexterous and user-friendly rehabilitation platforms is the next challenge to be tackled. We built a novel platform that uses an electro-encephalograpy-based BMI to control a multi-degree of freedom exoskeleton in a rehabilitation framework. Its applicability to a clinical scenario is validated here with six healthy subjects and a chronic stroke patient using motor imagery and movements attempts. Therefore, this study presents a potential system to carry out fully-featured motor rehabilitation therapies.

1 Introduction

Electro-encephalographic (EEG)-brain machine interfaces (BMIs) have previously been used to control an external robot or exoskeleton in assistive and rehabilitation frameworks [1, 3, 4]. Several decoding methods and training protocols have been tested to develop an efficient rehabilitation therapy with motor recovery. Despite the

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limitations of EEG technology and the moderated performance of EEG-decoding methods, the aforementioned studies demonstrated the potentiality of EEG-based BMIs as a tool for post-stroke rehabilitation. The focus has lately turned towards the development of BMI-based rehabilitation platforms that allow a more natural and dexterous control of multiple degrees of freedom (DOFs), and boost motor recovery.

In this study we present an EEG-based BMI platform for the control of a multi-DOF exoskeleton (Tecnalia, Spain) in a rehabilitation framework. The platform combines EEG-decoding methods proven to induce significant motor recovery [4] with a control platform and a rehabilitation exoskeleton that allows the training of complex functional tasks, involving several DOFs of the arm, wrist and hand. The rehabilitation platform is described and validated here with 6 healthy subjects and a chronic stroke patient, who followed a motor imagery and a motor attempt procedure, respectively.

2 Methods

2.1 Experimental Protocol

Six healthy participants (3 female, age 24–30, all right handed) and a chronic stroke patient suffering from a right hemiparesis (male, 67 years old, 3 years from stroke) participated in the study. All of them were naive to motor imagery/attempt and gave written consent to the procedures approved by the ethics committee of the Faculty of Medicine of the University of Tübingen, Germany.

They underwent a single session consisting of two parts: a screening phase and a real-time BMI operation phase. The data collected during the initial phase was employed to select the electrodes and frequency bands that would constitute the input to the BMI. During the second part, the participants controlled a 7-DOF exoskeleton using an EEG-based BMI in real-time. The exoskeleton was placed over a mat and allowed movements in 7-DOFs (details in [5]).

During the screening phase, the participants were asked upon auditory and visual cues to either imagine their right hand opening and closing (in case of the patient to try to open and close his paretic hand) or to relax for 5 s. Healthy subjects and the patient completed 5 and 3 blocks amounting to 55 and 33 trials of each condition, respectively. During the real-time phase, participants performed functional movements towards four different positions in the worskpace (see Fig. 1), while sitting and wearing the exoskeleton on their right upper limb. More precisely, they were instructed, by means of imperative auditory cues, to imagine/to attempt to reach a target while opening their hand and pronating their wrist and then back to a predefined rest position. Trials always started with a rest period of 3–5 s, followed by an auditory cue, a 2 s-long preparation time and a movement period. The maximum length of the movement period was 7 s. If the target position was not reached within this time, the same target position was kept for the next trials until reaching it in

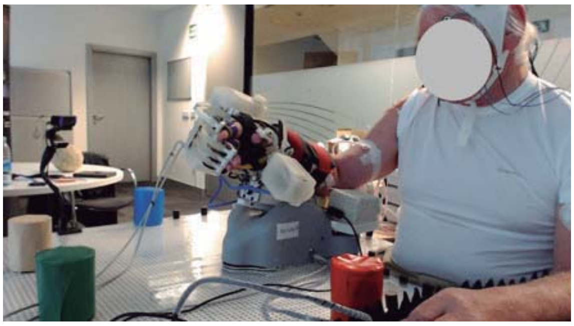

Fig. 1 A hemiparetic stroke patient controlling the 7-DOF exoskeleton with the EEG-BMI. The patient's arm is at the initial rest position and the colored cylinders define the four target positions around the workspace

all the DOFs. Otherwise, the trial ended as soon as the target was reached and subjects were instructed to head to the next position. The healthy subjects completed 5 blocks comprising 8 reached targets each, while the stroke patient performed 3 of those blocks.

2.2 Data Collection and Processing

EEG data from 32 channels: FP1, FP2, F7, F3, Fz, F4, F8, FC5, FC1, FC2, FC6, T7, C3, Cz, C4, T8, TP9, CP5, CP1, CP2, CP6, TP10, P7, P3, Pz, P4, P8, PO9, PO10, O1, Oz, O2 and two EOG channels were collected at 1 kHz (Brain Products GmbH, Germany). EEG signals were bandpass filtered (5–80 Hz), notch-filtered at 50 Hz and spatially filtered with a short-Laplacian filter. An autoregressive model of order 20 and its power was computed using 0.5 s-long windows and a step window of 50 ms. Finally, the mean power within the chosen frequency bands and electrodes were used as input features for the classifier. Kinematic activity of the above mentioned DOFs was recorded at 20 Hz with an optical symbol recognition system and motor encoders [5].

2.3 Real-Time Decoding and Operation of the Exoskeleton

The electrodes and frequency bands used as input to the BMI were selected based on a visual inspection of the r-squared coefficients obtained when comparing the sensorimotor rhythms (SMR) from the EEG activity recorded during the "relax" and "movement" screening trials. Features were computed on those electrodes and bands, as described in Sect. 2.2 and fed to the classifier in real-time. Linear discriminant analysis was used to classify the input features as "Movement" or "Rest". The classifier was trained using the screening data and then, retrained online at the end of each trial using the last two minutes of data from each condition. The outputs of the classifier were ignored during the rest and preparation periods, in which the exoskeleton remained still. However, during the movement period, if the output was classified as “Movement” (i.e. the participant produced a desynchronization of his/her pre-identified SMR), the exoskeleton moved his/her right arm towards one of the target positions along a predefined trajectory adjusted to his/her range of motion. On the other hand, outputs classified as “Rest” prevented the exoskeleton from moving. To achieve a more stable control and avoid twitching movements due to EEG signal noise, the current condition (i.e. exoskeleton in motion or in rest) was held as long as the decoder didn’t classify 5 consecutive outputs of the other condition, following [4].

To measure the performance offline, we analyzed the true positive rate (TPR), which represents the percentage of time the robot was moving (i.e. percentage of outputs classified as “Movement”) during the movement period, in which participants received feedback. Additionally, we compared this TPR to the false positive rate (FPR: percentage of outputs classified as “Movement” during the rest period).

3 Results

The mean TPR for all the healthy subjects was 62.8 ± 10.4 % and for the stroke patient was 54.9 %. The difference between the TPR and FPR (healthy subjects: mean = 39.8 ± 7.3 %; patient: 43.6 %) was significant ($p = 0.018$). In addition, all the healthy subjects and the stroke patient could successfully operate the exoskeleton in real-time using the EEG-BMI and accomplish all the trials.

4 Discussion and Conclusions

This study presents and validates a novel control platform based on an EEG-BMI that links brain activity with the movement of a 7-DOF rehabilitation exoskeleton in real-time. The results show that the TPR was significantly higher than the FPR. Although the performance of the decoder was not high, it should be taken into account that all the subjects were naive to motor imagery and a higher performance and more skillful control could be expected after several training sessions. Nevertheless, it is not clear how strong the correlation between decoding performance and level of recovery is. In fact, Ramos-Murguialday et al. [4] demonstrated that the algorithm used here, albeit not the most accurate one, could serve to elicit certain degree of motor recovery, in combination with a dedicated BMI-based rehabilitation therapy. This is the only double-blinded study that showed an EEG-BMI based therapy that induced motor recovery in chronic stroke patients. Therefore, although several algorithms could be used to decode EEG signals as part of a BMI system, we chose this one.

We have demonstrated that the participants were able to control the movement of the exoskeleton in real-time. Therefore, this system constitutes a potential rehabilitation platform for various reasons: (i) it establishes a contingent link between the movement intention decoded from the brain activity and the actual movement of the paralyzed limb; (ii) it provides a rehabilitation scenario in which functional movements towards various targets as well as the interaction with objects are possible; (iii) it allows for the rehabilitation of distal and proximal joints, proven to be beneficial [2]; (iv) even patients with no residual movement at all could benefit from it; (v) it can integrate other biosignals [5] and establish a hybrid control.

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