# Design and Comparative Evaluation of a BCI-based Upper Extremity Robotic Rehabilitation Protocol

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***Abstract*—We advocate online modification of robot-assisted task speed, based on continuously inferred motor imagery as an effective rehabilitation protocol for increasing the involvement levels of the patients in physical rehabilitation exercises. To study efficacy of such Brain-Computer Interface (BCI) based physical rehabilitation protocols, we conduct human subject experiments on healthy volunteers, comparing several BCI-based protocols with haptic and visual feedback with each other and with conventional robot-assisted rehabilitation protocols, in terms of intensity and sustainability of motor imagery. Our results provide evidence that the online adjusted BCI-based robotic protocol helps subjects produce stronger and more sustained motor imagery throughout the motor task, compared to other BCI-based protocols. We also show that BCI-assisted robotic therapy can enable a level of motor cortical activity that is similar to a scenario in which the subjects could actually execute the motion. These results suggest that BCI-assisted rehabilitation methods that provide online modification of the task speed based on continuously inferred motor imagery have potential in increasing the level of involvement of patients during exercises and may lead to more effective recovery.**

## I. Introduction

In recent years, design methodologies for rehabilitation robots have matured and robotic systems for rehabilitation have become ubiquitous. Clinical trials on robotic rehabilitation provide evidence that robotic therapy is effective for motor recovery and possesses high potential for improving the functional independence of patients [1]–[3]. To increase the efficacy of robot assisted therapies, there is still a pressing need for evidence based therapy protocols and novel systematic approaches to safely deliver these therapies.

State-of-the-art rehabilitation robots regulate the physical interaction between the patient and the device to measure the active involvement of patients and motivate them to actively contribute for the therapy sessions. These "assist-as-needed" protocols aim to minimize the assistance given to patients, therefore they supply only required amount of assistance to achieve safety and progress. Most of the rehabilitation systems in the literature require the voluntary muscle control as the contribution of the subject; however, patients with severe disabilities (e.g. spinal cord injured patients) may have difficulties to perform physical actions due to their disability levels.

Bypassing the impaired neuromuscular system and monitoring the current state of the brain activity, Brain-Computer Interface (BCI) based rehabilitation protocols can be applied to patients with severe disabilities to effectively induce activity-dependent brain plasticity and to restore neuromuscular function. BCI systems can create gateways between the mental states of patients and rehabilitation protocols, by measuring the brain activity and classifying the measured activity to extract meaningful cues for physical rehabilitation. Even though there are multiple ways to monitor the brain activity, non-invasive electroencephalogram (EEG) is the favored method for rehabilitation due to its portability and ease of use [4], [5]. EEG signal measurements emphasize sensorimotor rhythms that occur in a correlated fashion with the user's intent. Thanks to such correlation, a EEG-based BCI system processes EEG signals and automatically recognizes underlying patterns, such as intention of the users to move.

Clinical studies show evidence that patients with disabilities are capable of operating motor imagery (MI) based BCI tasks as efficiently as healthy volunteers [6]. BCI systems have been used as a part of physical rehabilitation studies using virtual games [7], [8], the visual feedback of the movement of robotic devices [9], [10] or haptic feedback [6], [11], [12] where the BCI outputs are used to trigger the movement of upper limb rehabilitation devices. An experimental procedure has been designed in [13] such that the users are either guided by the rehabilitation device or to control the movements of the device through attempting real/imaginary movement in every 300 ms to synchronize the system with users' intentions. Previously, we proposed a novel, systematic approach to enable online modification/adaptation of robot-assisted rehabilitation exercises by continuously monitoring intention of users, where the posterior probabilities of EEG data extracted from Linear Discriminant Analysis (LDA) classifier are used as continuous-valued outputs to control the speed of a rehabilitation robot [14]. Passive Velocity Field Controller (PVFC) is used to ensure coupled stability of the human-robot system, while modifying the task speed of the haptic device during the exercise with respect to intention levels of users in an online manner. This protocol awards an increase in the level of user "intention" with a higher task speed to encourage active participation in therapies.

As the literature gets wider with different designs of BCI-based rehabilitation protocols in terms of the feedback type or integration method of the BCI systems, the necessity to conduct comparison studies increases. The effect of haptic feedback over virtual feedback in a BCI-based rehabilitation system is studied in [13] with the results favoring the robotic

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feedback for both training and testing blocks in terms of ERD and motor task classification performance based on EEG data. Experiments to compare different protocols such as patient passive, patient active, BCI-with-feedback and BCI-no-feedback have been presented in [15] for healthy volunteers and in [16] with chronic stroke patients. The results of these studies favor the use of BCI in a manner similar to the protocol we use in this work. In our work, we also compare several BCI-based protocols.

The focus of this paper is to study the efficacy of the BCI-assisted robotic rehabilitation protocol [14] comparing to other BCI-based protocols and conventional robot-assisted rehabilitation protocols in a simple reaching exercise. For this purpose, we conduct human subject experiments on healthy volunteers, comparing several BCI-based protocols with and without haptic feedback with each other, and with conventional robot-assisted protocols, in terms of intensity and sustainability of motor imagery during motor tasks. In particular, we investigate

- the impact of robotic assistance with haptic feedback on BCI performance,
- the efficacy of online modification of assistance based on continuously monitored BCI versus utilizing BCI to trigger movements, and
- the impact of the presence of BCI in the rehabilitation protocol on the motor cortical activity of the subjects.

## II. Rehabilitation Protocols

In this study, six different rehabilitation protocols $P_i$ $(i = 1, .., 4)$, $PA$ and $PP$ are compared:

$P_1$ – *BCI-assisted Robotic:* Volunteers are asked to execute right arm MI to move a robotic rehabilitation system. As we proposed in [14], the BCI outputs are calculated by averaging the binary outputs in moving windows of 1 s length, in order to obtain continuous-valued outputs. The first 500 ms and the last 250 ms of a trial are not included in this calculation. The obtained continuous-valued BCI outputs determine the task speed of the robot movements.

$P_2$ – *BCI-assisted VR:* Volunteers are asked to execute right arm MI to move a virtual object displayed on a computer screen. BCI outputs are calculated the same way as in $P_1$ and used to determine the task speed of the virtual object.

$P_3$ – *BCI-triggered Robotic:* Volunteers are asked to initiate the movement of the robotic rehabilitation system through right arm MI. During a waiting phase with a duration between 500 ms and 10 s, the volunteers are asked to perform right arm MI. Once the intention levels exceed a predetermined threshold in the waiting phase, the robot is moved with a constant speed until the end of the trial. The intention of the volunteers are not evaluated for the rest of the trial, once the motion is triggered.

$P_4$ – *BCI-triggered VR:* Volunteers are asked to initiate the movement of a virtual object displayed on a computer screen through right arm MI. BCI outputs are calculated the same way as in $P_3$ and used to initiate the movement of a virtual object with constant speed.

$PA$ – *Protocol Active:* Volunteers are asked to complete the same task by applying physical forces to the end-effector of the rehabilitation robot. In this protocol, volunteers actively take part in the task, physically executing the task without any assistance. The BCI system is used only to measure the intention levels of subjects for the following comparisons.

$PP$ – *Protocol Passive:* The rehabilitation robot guides the arm of the volunteer at a constant speed to complete the same desired task. No physical and mental contribution is required from the volunteer for the task to be completed. The BCI system is used only to measure the intention levels of subjects for the following comparisons.

## III. BCI-Based Robotic Rehabilitation System

Fig. 1. shows the BCI-based robot assisted rehabilitation system setup which has already been detailed in [14]. This system consists of:

Fig. 1. Experimental setup consisting of the Biosemi ActiveTwo EEG measurement device and AssistOn-Mobile

*Real-Time BCI System*: A Biosemi ActiveTwo EEG System is used to measure the electrical activity of the brain to achieve the continuous, real-time processing of user intention. The LDA algorithm is used to classify the ERD/ERS patterns in EEG signals as “move” or “rest’. The LDA classifier parameters are learned through training blocks. In testing blocks, the real-time BCI system provides binary classification outputs in every 250 ms by classifying these patterns. These binary outputs are used directly for “BCI-triggered” protocols. To obtain continuous-valued outputs for “BCI-assisted” protocols, binary outputs of the LDA classifier are averaged in a moving window of 1 s. Nevertheless, the presence of training blocks, in which the EEG signals are modelled for each subject, is a requisite before testing blocks to recognize the ERD/ERS patterns.

*Rehabilitation Robot*: To administer robot assisted therapies, AssistOn-Mobile [17], [18], a mobile rehabilitation robot with unlimited planar workspace, is used for upper limb rehabilitation exercises. AssistOn-Mobile is an active holonomic mobile platform based multi-DoF series elastic actuator, designed to administer therapeutic table-top exercises to patients. In particular, it consists of a 3 DoF planar, compliant parallel mechanism coupled to a Mecanum-wheeled mobile platform to result in a multi-DoF series-elastic actuator.

*Contour Following Tasks and Passive Velocity Field Controller*: Contour following tasks are selected as the therapeutic exercises, since they are favorable in rehabilitation due to its property that decouples the task from the speed of the task. Therefore, coordination and synchronization between various degrees of freedom can be emphasized, while exact timing along the path is left to the preference of the user. As a contour following controller, PVFC is used, since it can ensure coupled stability of the overall system throughout the therapy, while providing a systematic way to modify task parameters such as task speed, difficulty, and amount of assistance [19]. For BCI integration, the intention levels of subjects are mapped to the speed parameters used by PVFC and synchronized to the speed of ASSISTON-MOBILE.

*Visual Feedback Module*: Visual feedback is provided to users during BCI training and during therapy sessions to help them visualize the desired contour and their current location with respect to this contour.

## IV. EXPERIMENTAL PROCEDURE

A human subject experiment is designed to compare the efficacy of the six protocols presented in Section II. 13 right-handed healthy subjects participated voluntarily to one session of the experiment, in which they experienced all six rehabilitation protocols conducted sequentially, after signing an informed consent form. The order of protocols are randomized for each subject and regular breaks after the administration of each protocol are scheduled to prevent fatigue. Seven subjects among 13 have been extracted from the analysis due to their low data quality for at least two protocols. The remaining six subjects are five males and one female with ages between 24 and 29 years.

Each BCI protocol is composed of independent training and testing blocks, which consist of trials. The length of each trial is 13 s, "idle" phase of 8 s and "operating" phase of 5 s. The transition between these two phases is indicated by visual/audio cues. EEG signals collected during the idle phases do not affect the system performance and are not evaluated. Hence, volunteers are allowed to execute minor movements to prevent fatigue as long as they do not disturb their connection with the robotic device or the BCI system. During the operating phases of the training blocks, volunteers are asked either to rest or to execute right arm MI movements. On the contrary, during the operating phases of the testing blocks, volunteers perform only right arm MI movements, to result in a meaningful rehabilitation protocol. Fig. 2. presents the schematic representation of trials during training blocks (a) and testing blocks of BCI-assisted (b) or BCI-triggered (c) protocols. For the BCI-triggered protocols, a waiting phase with a duration between 500 ms and 10 s is inserted between idle and operating phases. During the waiting phase, volunteers are asked to perform right arm MI. This phase transitions to operating phase once the intention levels exceed a predetermined threshold.

The training and testing blocks have 11 and 15 trials, respectively. The first trial of the training block contains a MI task to remind the volunteer about the current protocol. Nevertheless, data collected at this first trial is eliminated from the analysis to ensure equal size of MI and rest trials for each task.

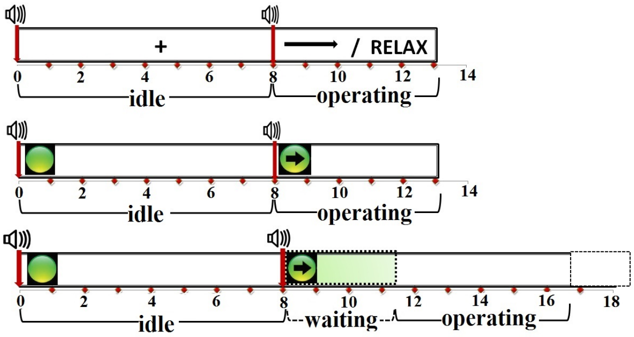


Fig. 2. Idle, operating and waiting phase timing scheme in seconds for a (a) training block, (b) testing block of BCI-assisted protocols, (c) testing block of BCI-triggered protocols.

The quality of EEG training data directly affects the performance of the classifier and consequently the efficacy of the BCI system. Moreover, the positive impact of the robotic assistance on the training data has been observed in [13]. Based on this result, training blocks of BCI-triggered robotic and BCI-assisted robotic protocols provide haptic assistance to the volunteers with a constant speed during the MI tasks. In these robotic training trials, the device moves forward during the MI tasks while turns back to the initial position during the following idle phase. In contrast, there exists no robotic motion in the training block of VR protocols.

## V. EEG DATA RECORDING AND ANALYSIS

EEG signals were measured over $C_3$, $C_z$, $C_4$ locations of the international 10-20 electrode placement system, at 2048 Hz sampling rate (see Fig. 3.) using a Biosemi ActiveTwo EEG System. By subtracting the average of the data received from their anterior and posterior channels ($CP_3$, $FC_3$ for $C_3$, $CP_z$, $FC_z$ for $C_z$ and $CP_4$, $FC_4$ for $C_4$), three referenced channels are obtained.

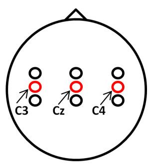


Fig. 3. Positions of the electrodes used in the experiments.

Our analysis focuses on data collected by the $C_3$ channel, since the right arm MI tasks are correlated with the left side of the brain, due to the laterality of the brain [20], [21].

### A. Feature Extraction

While performing MI, ERD, which is related to the imagination of the motor tasks [21], occurs and changes the amplitude of the signal. ERD is characterized by the power spectral density (PSD) computed in the typical EEG $\alpha$ (8-12 Hz) frequency band. In order to analyze the $\alpha$ frequency band, Short Time Fourier Transform is applied to data collected during each trial. Knowing that MI causes smaller PSD values due to ERD phenomena, the active participation level of the users can be achieved by investigating the PSDs over time.

### B. Evaluation Metrics

In order to compare rehabilitation protocols, testing blocks have been analyzed using two metrics. Firstly, the averaged PSD values obtained from the $C_3$ channel across the subjects as a function of time for each protocol have been studied. In addition, one tailed t-tests, where results less than $0.05$ reported as statistically significant, are applied to PSD data of each volunteer for $4$ time windows $(0-1, 1.25-2.25, 2.5-3.5, 3.75-4.75\ \ \text{s})$ in each trial. Secondly, the average classification performance over all time windows for each volunteer is calculated to support the obtained inferences.

## VI. Results and Discussion

Fig. 4. presents the logarithm of averaged PSD values between the second and the third seconds of the operating phase as a function of frequency. The peak in the figure indicates ERD in the $\alpha$ frequency band. It can be observed from the figure that our proposed protocol ($P_1$) achieves ERD level as strong as actual active movement ($PA$) and stronger than all of the other protocols. This observation suggests that the proposed BCI-assisted robotic rehabilitation protocol ($P_1$) ensures active mental involvement of the subjects in the motor task.

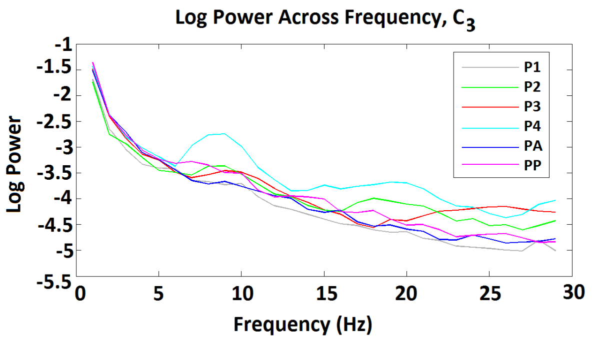


Fig. 4. Log power values of the protocols obtained from the $C_3$ channel.

The testing blocks have been analyzed and compared to each other using two metrics as defined in Section V-B. Fig. 5. presents the averaged values from the $C_3$ channel across the subjects as a function of time for each protocol. The results of t-tests applied to PSD data of each volunteer for four time windows in each trial are given in Table I. These results are discussed below from four different perspectives:

TABLE I. Results of One Tailed t-Tests (p values)

| | 0–1 s | 1.25–2.25 s | 2.5–3.5 s | 3.75–4.75 s |
|---|---|---|---|---|
| $P_1 < P_2$ | **2.17E-05** | **0.000801** | **0.008295** | **0.000103** |
| $P_3 < P_4$ | **0.016046** | **6.64E-05** | **4.7E-08** | **5.2E-09** |
| $P_1 < P_3$ | 0.12701 | **0.001001** | **0.012594** | **0.001346** |
| $P_2 < P_4$ | 0.951512 | **0.000143** | **5.15E-06** | **1.06E-07** |
| $PA < P_1$ | 0.823217 | 0.797126 | 0.765011 | 0.978540 |
| $P_1 < PP$ | **0.002824** | **0.001112** | **0.00206** | **0.003573** |
| $PA < PP$ | **0.040901** | **0.001749** | **0.008047** | 0.094319 |

### A. *Impact of Haptic Feedback on Cortical Activity*

The impact of the haptic feedback provided by the robot during the testing blocks have been investigated for BCI-assisted protocols ($P_1$ - $P_2$) and BCI-triggered protocols ($P_3$ to $P_4$). Note that the protocols with robotic assistance ($P_1$ and $P_3$) employ the robot during both the training and testing blocks as suggested in [13], while only visual feedback is provided during the VR protocols ($P_2$ and $P_4$).

The log power values in the $\alpha$ frequency band of BCI-assisted VR protocol ($P_2$) have been observed to be greater than BCI-assisted robotic protocol ($P_1$) from Fig. 4. In a similar manner, log power values of BCI-triggered VR protocol ($P_4$) have been greater than BCI-triggered robotic protocol ($P_3$). These results indicate that ERD suppression is more effective for robotic protocols that involve haptic feedback, implying better average concentration levels of subjects.

Further analysis of PSD values for each protocol have been presented as Fig. 5. From the figure, it is clear that the suppression in $\alpha$ band have occurred earlier in BCI-assisted robotic protocol ($P_1$) than in BCI-assisted VR protocol ($P_2$), which indicates that the use of robot assistance in a rehabilitation protocol might have the potential to make the subjects get involved in the tasks earlier. As the time progresses, the suppression has been better sustained in ($P_1$) as compared to ($P_2$). Similarly, the PSD plots in Fig. 5. indicate that the ERD suppressing in the BCI-triggered robotic protocol ($P_3$) has been more intense and better sustained than that of the BCI-triggered VR protocol ($P_4$).

As the most compelling evidence of these observations obtained from the averaged data, one tailed t-tests have been applied to investigate the difference of the PSD values in different protocols for each subject and each trial. The t-test results in Table I show that, the PSD values of BCI-assisted Robotic protocol ($P_1$) have been statistically significantly smaller than that of BCI-assisted VR protocol ($P_2$) for all time windows. Similarly, one tailed t-test results comparing BCI-triggered Robotic protocol ($P_3$) to BCI-triggered VR protocol ($P_4$) indicate that the PSD values of ($P_3$) have been statistically significantly smaller than those of ($P_4$) throughout the whole movement.

These results might imply that the robotic protocols have stronger ERDs than virtual protocols due to the haptic feedback provided to the subjects. Henceforth, the haptic feedback provided through robotic movement appears to enhance the MI activity observed in the motor cortex under both BCI-assisted and BCI-triggered protocols. This finding suggests the potential of haptic feedback in improving the BCI performance.

### B. *Efficacy of Continuous vs Triggered BCI Protocols*

Another investigation has been performed about the effect of the continuous use of the BCI system throughout the desired task compared to the triggered BCI protocols, in terms of participation levels of subjects. With this motivation, robotic feedback protocols ($P_1$ to $P_3$) and virtual feedback protocols ($P_2$ to $P_4$) have been compared separately.

Fig. 4. shows that BCI-assisted Robotic protocol ($P_1$) has resulted lower log power values in the $\alpha$ band compared to those of BCI-triggered robotic protocol ($P_3$). Similarly, BCI-assisted VR protocol ($P_2$) has displayed better suppressing

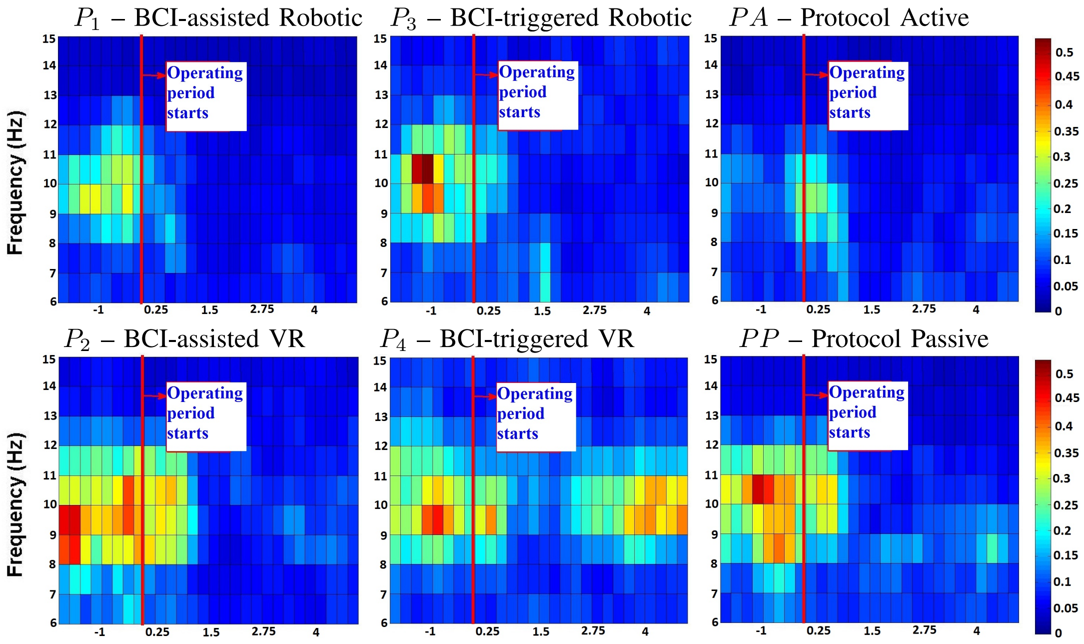


Fig. 5. PSD values of signals obtained from the $C_3$ channel across time for all six rehabilitation protocols.

performance than BCI-triggered VR protocol ($P_4$) in the $\alpha$ band. These observations favor the continuous use of BCI during MI with online modification of the task speed, rather than employing BCI only to trigger motion, for both haptic and visual feedback protocols.

Further analysis of PSD values and the one tailed t-test results for each protocol have been presented as Fig. 5 and Table I. From the figure, it is clear that ERD in BCI-assisted Robotic protocol ($P_1$) has been more intense than in BCI-triggered robotic protocol ($P_3$). Moreover, the t-test results in the mentioned table quantify the difference between these PSD values and indicate statistically significant difference between the two protocols, in all but the first time window. Similarly, ERD in the BCI-triggered VR protocol ($P_4$) has been discontinuous while PSD values in this protocol have been larger compared to the case in BCI-assisted VR protocol ($P_2$), as time progresses. The t-test results show that these two protocols are not significantly different for the first time window, while they are statistically significantly different in the other three time windows, with PSD values in the continuous feedback protocol being significantly smaller than in the triggered protocol. Even though both protocols start of with similar ERD levels, the sustained ERD in BCI-assisted protocols as time progresses provides evidence that subjects tend to disengage from the task in BCI-triggered protocols especially time progresses, while BCI-assisted protocols are significantly more effective in engaging the user in the physical therapy exercise.

Comparing the two different ways to use BCI for rehabilitation (continuous use during the movement with online modification of the task speed versus triggering the movement) with haptic and virtual feedbacks leads us to the conclusion that the continuous use of BCI might be beneficial for subjects to remain continuously involved in their tasks.

### C. *Impact of Adding BCI to Robotic Rehabilitation Protocols*

The previous subsections indicate improved efficacy of BCI-assisted Robotic protocol in terms of keeping users active throughout the movement. Yet, the investigation of the impact of such BCI-based rehabilitation protocol over the conventional robot-assisted rehabilitation protocols are required to complete the proposed study. Therefore, we compare BCI-assisted Robotic protocol ($P_1$) to Protocol Active $PA$ and Protocol Passive $PP$ protocols.

Analysing Fig. 5. indicates that the averaged PSD values of Protocol Passive $PP$ have been greater than Protocol Active $PA$ and BCI-assisted Robotic protocol $P_1$. Consequently, these results imply that protocols $P_1$ and $PA$ lead to more intense MI than $PP$. On the other hand, PSD plots between $PA$ and $P_1$ do not display any difference. Moreover, log power values of $P_1$ have found similar to those of $PA$ as shown in Fig. 4. The one tailed t-test results in Table I have quantified these observations, indicating that PSD values of $P_1$ are statistically significantly smaller than those of $PP$ for every time window. Furthermore, PSD values of $P_1$ and $PA$ are not significantly different for all time windows, except the last one.

Given that the Protocol Active $PA$ is the golden standard in robot-assisted rehabilitation in terms of ensuring the active participation of subjects throughout the therapy, the t-test results for the BCI-assisted Robotic protocol $P_1$ suggest that the proposed protocol with online modification of the task speed of a rehabilitation device based on continually monitored EEG signals has the potential to achieve uninterrupted active participation levels of users that are comparable to active limb movements of the subjects. Overall, these results suggest that BCI-assisted robotic therapy can enable motor cortical activity, similar to a scenario in which the users could actually execute the motion by themselves, and much stronger than the activity produced in conventional

TABLE II. PERCENT CLASSIFICATION ACCURACY

| | $P_1$ | $P_2$ | $P_3$ | $P_4$ |
|---|---|---|---|---|
| S1 | 94.5098 | 92.15686 | 93.72549 | 61.56863 |
| S2 | 98.03922 | 92.94118 | 97.64706 | 68.23529 |
| S3 | 84.70588 | 85.09804 | 43.13725 | 81.96078 |
| S4 | 95.29412 | 34.90196 | 90.19608 | 71.76471 |
| S5 | 84.70588 | 93.72549 | 99.21569 | 71.76471 |
| S6 | 68.23529 | 74.5098 | 78.82353 | 70.58824 |
| Average | **87.5817** | **78.88889** | **83.79085** | **70.98039** |

patient-passive rehabilitation protocols commonly employed for severely injured patients.

### *D. Classification Accuracy*

Average motor imagery (MI) classification performance based on EEG data over all time windows for each subject is presented in Table II, as the confirmation of the first two analyses. Note that the features used in classification are the PSDs, so the classification results are expected to support the findings of the previous sections. According to Table II, the classification accuracies (ACC) of the protocols might be ordered as $ACC_{P_1}>ACC_{P_3}>ACC_{P_2}>ACC_{P_4}$ and this order indicates the positive impact of haptic assistance $(ACC_{P_1,P_3}>ACC_{P_2,P_4})$ and the online modification of the task speed $(ACC_{P_1}>ACC_{P_3},\ ACC_{P_2}>ACC_{P_4}$.

## VII. CONCLUSION

We have presented the design and experimental evaluation of a BCI-based robotic rehabilitation protocol for upper extremity and compared its performance on healthy volunteers with conventional robotic rehabilitation protocols, in terms of active involvement of the subjects in motor tasks, as measured by the strength of MI. Of particular interest is the efficacy of the proposed BCI-assisted Robotic rehabilitation protocol that involves online modification of the task speed. Our results provide statistical evidence that such BCI-assisted Robotic rehabilitation protocol exhibits significantly better performance than (a) protocols involving only visual feedback, (b) BCI-triggered robotic rehabilitation protocols and (c) conventional, patient-passive robot-assisted rehabilitation protocols. Our work demonstrates the potential for using such BCI-based protocols for rehabilitation purposes, while also motivating further experimentation and analysis.

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