Brain Computer Interface based Robotic Rehabilitation with Online Modification of Task Speed

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***Abstract*—We present a systematic approach that enables online modification/adaptation of robot assisted rehabilitation exercises by continuously monitoring intention levels of patients utilizing an electroencephalogram (EEG) based Brain-Computer Interface (BCI). In particular, we use Linear Discriminant Analysis (LDA) to classify event-related synchronization (ERS) and desynchronization (ERD) patterns associated with motor imagery; however, instead of providing a binary classification output, we utilize posterior probabilities extracted from LDA classifier as the continuous-valued outputs to control a rehabilitation robot. Passive velocity field control (PVFC) is used as the underlying robot controller to map instantaneous levels of motor imagery during the movement to the speed of contour following tasks. In other words, PVFC changes the speed of contour following tasks with respect to intention levels of motor imagery. PVFC also allows decoupling of the task and the speed of the task from each other, and ensures coupled stability of the overall robot patient system. The proposed framework is implemented on** ASSISTON-MOBILE**—a series elastic actuator based on a holonomic mobile platform, and feasibility studies with healthy volunteers have been conducted test effectiveness of the proposed approach. Giving patients online control over the speed of the task, the proposed approach ensures active involvement of patients throughout exercise routines and has the potential to increase the efficacy of robot assisted therapies.**

I. INTRODUCTION

In recent years, design methodologies for rehabilitation robots have matured and robotic systems for rehabilitation have become ubiquitous. Clinical trials investigating efficacy of robotic rehabilitation provide evidence that robotic therapy is effective for motor recovery and possesses high potential for improving functional independence of patients [1]–[4]. However, to further increase 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. In this paper, we focus on Brain Computer Interfaces (BCI) in robot assisted neurological rehabilitation and propose a systematic framework to integrate BCI with rehabilitation robots such that active participation of patients, especially patients with severe motor disabilities, in the therapy session is assured.

Since active participation of patients in therapies is known to be crucial for motor recovery, state-of-art rehabilitation robots regulate the physical interaction between the patient and the device. These systems require patients to do positive work on the system such that movement exercises can be completed. These control techniques are commonly extended with "assist-as-needed" protocols to provide minimal assistance to the patient, since redundant amount of assistance is shown to be detrimental for recovery, while proper amount of assistance is necessary to ensure safety and progress.

Even though active rehabilitation devices can impose forces/movements to patients with all levels of impairment, it is not trivial to extend adaptive assistance protocols to patients with severe disabilities. In particular, severe motor disability of these patients preclude their voluntary muscle control and physical contribution to the task, on which most of the current "assist-as-needed" protocols depend. Bypassing the impaired neuromuscular system and enabling monitoring of the current state of brain activity, BCI technology promises an alternative pathway to guide rehabilitation protocols to effectively induce activity-dependent brain plasticity and to restore neuromuscular function. In the literature, it has been shown that stroke patients are capable of operating a motor imagery based BCI system as efficiently as healthy subjects [5].

Recently, there has been much interest in developing BCI technology to help restore function for patients with severe motor disabilities [6]–[8], including patients with severe trauma due to stroke, cerebral palsy, or injury to spinal cord or brain. These studies commonly rely on non-invasive electroencephalogram (EEG) signals, since collecting these electric potentials is more practical, less expensive, and safer for the patients, compared to invasive techniques.

Rehabilitation therapy using EEG-based BCI systems can be loosely categorized into two: systems that only represent movements corresponding to motor imagery, typically in a virtual reality (VR) environment, and systems that physically interact with the patient to impose movement therapies corresponding to the motor imagery. Belonging to the first category, in [9]–[11] mental imagery experiments have been conducted on healthy subjects and/or stroke patients. The subjects are asked to imagine a movement while observing corresponding visual feedback in a VR environment. These feasibility studies show that stroke patients can control virtual movements with a BCI system as well as healthy subjects. In [12], [13] mental imagery experiments have been completed on healthy subjects by providing visual feedback through a physical robotic device instead of a VR environment. In these experiments, subjects control the movements of a robotic arm without having any physical contact with the device. In [12], it is shown that visualization of the physical robot improves the accuracy of the final decision about the task, while [13] presents feasibility of different control architectures.

In the second category, rehabilitation robots are integrated with BCI to impose necessary therapeutic exercises. For instance, [14]–[16] conduct experiments on healthy subjects and/or stroke patients asking them to imagine moving their arms and use EEG classifications obtained from ERD/ERS patterns to trigger the movement of a rehabilitation robot. In [14], ERD/ERS patterns are classified as "move" and "rest" using Naive Bayes Parzen Window to trigger reaching movements with MIT-Manus robot. In [15], CSP filter classifies "move" and "rest" commands to trigger reaching tasks with Light-Exos. In this study, trajectories are generated with an online method to desired targets that the subjects can choose using an eye-tracking system. In [16], Filter Bank Common Spatial Pattern algorithm classifies "go" and "rest" commands to trigger MIT-Manus for reaching tasks. Studies [17] and [18] present clinical studies for the BCI integrated rehabilitation system in [16]. These studies demonstrate feasibility of BCI integrated rehabilitation robotics. Moreover, results indicate a better classification accuracy for mental imagery with haptic feedback when compared with providing only visual feedback.

However, in all of these BCI integrated rehabilitation robot systems, patients' intentions have only been used to initiate and stop the movement therapy. With these approaches, once the movement is triggered, the patient may stop focusing on the movement until the next task. Besides, after a threshold is overcome, the resulting movement is always the same, invariant of the amount of effort the patients put in to imagine the movement. As a result, these systems cannot ensure active participation of patients in the movement therapy. Recently, [19] advocates the importance of real-time adaptation of movement therapies to correspond with the patients' intention captured by EEG-based BCI. Even though this study provides initial feasibility studies showing two stroke patients controlling a Barrett WAM robot attached to their impaired arm, the real-time adaptation of therapies based on BCI classification has been left as a part of their future work. Similarly, in [20] intentions of the subjects are decoded every 300 ms and the state of the robot is updated either in a passive mode where the subjects are instructed to attempt a real/imaginary movement, or in an active mode where the subjects' movements are guided by the device. Updating the robot state every 300 ms enables the system to be synchronized with subjects' intentions. Welch's method has been used to compute estimates for the power spectral density to classify the user's intention as "go" or "rest".

The main contribution of this paper is a systematic approach that enables online modification/adaptation of robot assisted rehabilitation exercises by continuously monitoring intention of patients utilizing EEG-based BCI. In the proposed approach, the LDA algorithm is used to classify ERD/ERS patterns of EEG signals as "move" or "rest", but instead of using this binary classification as the output to the robot controller, the posterior probabilities extracted from the LDA classifier are directly used as the continuous-valued outputs to control the rehabilitation robot. Therapeutic tasks are selected as contour tracking exercises where coordination and synchronization between various degrees of freedom are emphasized, while timing along the path is left to the patient. Passive velocity field control (PVFC) is used as the underlying robot controller, since PVFC not only allows decoupling of the task and the speed of the task from each other, but also does so by rendering the closed loop system passive with respect to externally applied forces, ensuring coupled stability of the overall robot patient system. In particular, continuous-valued outputs of the BCI system that correspond to the instantaneous levels of motor imagery during the movement guide the speed of the contour following task by directly adjusting the speed regulation parameter in PVFC. With increased level of "intention" (as reflected in the posterior probabilities of the classifier), PVFC increases the speed of the robot which provides useful feedback to the subjects to encourage active participation to complete the task. In addition to the speed of the task, our approach also allows for on-line modification of the task difficulty and the level of assistance as determined by the therapist [21]. Giving patients online control over the speed of the task, the proposed framework ensures active involvement of patients throughout the exercises and has the potential to increase the efficacy of robot assisted therapies. Our overall control architecture is implemented on a multi-DoF series elastic actuator, ASSISTON-MOBILE, developed for administering therapeutic table-top exercises to patients.

The paper is organized as follows. Section II introduces the main components that constitute the proposed BCI-based rehabilitation system. Section III describes the BCI component and provides details of offline, online sessions, and data analysis operations. Section IV reviews the rehabilitation robot, ASSISTON-MOBILE, used in our experiments, while Section V discusses utilization of PVFC to integrate BCI with robot assisted rehabilitation therapies. Section VI provides feasibility studies and experimental results. Finally, Section VII concludes the paper and discusses future work.

II. BCI-BASED ROBOTIC REHABILITATION SYSTEM

The proposed BCI-based robot assisted rehabilitation system consists of:

i. *Real-Time BCI System*: For real-time, continual processing of patient intention, a Biosemi ActiveTwo EEG System is used to measure the electrical activity of the brain. The LDA algorithm is used to classify ERD/ERS patterns in EEG signals as "move" or "rest'. Instead of using the binary classification outputs, the posterior probabilities extracted from the LDA classifier are directly used as the continuous-valued outputs, to control the speed of the therapeutic movements performed by the robotic system.

ii. *Rehabilitation Robot*: To administer robot assisted therapies a mobile rehabilitation robot with unlimited planar workspace, ASSISTON-MOBILE [22] is used. 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, ASSISTON-MOBILE 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.

iii. *Contour Following Tasks and Passive Velocity Field Controller*: Contour following tasks are selected as the therapeutic exercises. These tasks are favorable as rehabilitation exercises, since the task and the speed of the task can be decoupled from each other. This way, coordination and synchronization between various degrees of freedom can be emphasized, while exact timing along the path is left to the preference of the patient. As a contour following controller, PVFC is used, since this controller can ensure coupled stability of the overall system throughout the therapy, while also providing a systematic way to modify task parameters such as task speed, difficulty, and amount of assistance [21]. During BCI integration, PVFC enables intention level of patients to be synchronized to the speed of ASSISTON-MOBILE.

iv. *Visual Feedback Module*: Visual feedback is provided to patients during training and during therapy sessions to help them visualize the desired contour and their current location with respect to this contour. The visual feedback can be projected on the table to superimpose the desired task on the physical system.

III. BRAIN-COMPUTER INTERACTION

BCI generates commands by measuring the brain signals. There exist two methods of measuring the brain activity: the invasive method in which the electrodes are placed under the scalp by surgical operation, and the non-invasive method in which the electrodes are placed on a headcap which is worn by the subject and the brain signals are measured externally. Although the invasive method results in more accurate signals, the non-invasive method is obviously more practical and safer for the patients. EEG is one of the non-invasive methods which measures electrical activity of the brain. Although EEG is a noisy method, it is commonly favored for BCI applications, thanks to its portability, ease of use and low-cost. Given EEG signals measured in experiments designed to emphasize sensorimotor rhythms occurring in a correlated fashion with the user's intent, the goal is to process these signals and automatically recognize underlying patterns. ERD/ERS patterns [23], [24] can be observed to identify motor imagery movements where ERD is related to imagination of the motor tasks and ERS is related to the passive state. Recognizing these patterns of sensorimotor rhythms gives the opportunity to control cue-based synchronous or self-paced asynchronous BCI systems.

In the literature, linear and non linear methods have been proposed to classify motor imagery movements using ERD/ERS patterns as features [25]. Linear methods are commonly preferred, since they are generally more robust due to their lower complexity, stationarity structure, and consistency against overfitting [26]. Two main kinds of linear classifiers have been used in BCI research, namely, LDA and support vector machines (SVM), which result in similar performances. Consequently, in this work, LDA which is a fast, stationary classification method that is known to produce good results in motor imagery based BCIs [27]–[30], is used to classify motor imagery movements using ERD/ERS patterns.

A. Data Collection

For EEG recordings, a Biosemi ActiveTwo EEG System is used. The recording configuration shown in Figure 1 uses Ag-Cl electrodes at C_3, C_z, C_4 locations of the international 10-20 electrode placement system, at 512 Hz sampling rate. Their anterior and posterior channels are used as references. By subtracting the average of the data received from upper and lower neighbor channels of a main channel, three referenced main channels are obtained.

Once the EEG data are collected, they are analyzed as described below. In this work, we collect and analyze the data from healthy subjects as they imagine right arm movements.

B. Data Analysis

1) Feature Extraction: ERD and ERS are mainly characterized by the help of spectral powers computed in the typical EEG alpha (8Hz-13Hz), sigma (14Hz-18Hz) and beta (18Hz-30Hz) frequency bands related to the preparation of the imagery movements [23]. To analyze these frequency bands Short Time Fourier Transform is applied to each trial. The activity of the brain can be observed after the cue is shown. Hence, instead of analyzing frequency bands of the entire signal, a timing window is used. Afterwards, the average power spectral densities of the 3 selected frequency bands are calculated and selected as features. Therefore, 3 different spectral power densities are calculated for 3 different electrodes resulting in a 9-dimensional feature vector.

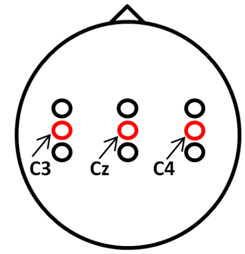

Fig. 1. Positions of the electrodes used in our experiments.

2) Classification: A classification problem which contains 2 classes (right arm imagery movement and rest period), is built and LDA which separates classes by using hyperplanes, is used as a classifier. The assumption made for the training data is, its 2 classes have multivariate normal density distributions. Training set classes are modelled to have the same covariance matrix but different mean vectors. These are estimated from the training data as shown in Eqns. (1) and (2).

$$\hat{\mu}_k = \frac{\sum_{i=1}^{N} M_{ik} x_i}{\sum_{i=1}^{N} M_{ik}} \tag{1}$$

$$\hat{\Sigma}_k = \frac{\sum_{i=1}^{N}\sum_{k=1}^{2} M_{ik}(x_i - \hat{\mu}_k)(x_i - \hat{\mu}_k)^T}{N-2} \tag{2}$$

If a sample x_i belongs to class k, the value of M_{ik} is 1, otherwise it is 0. A testing sample is classified by minimizing the expected cost value as shown in Eqn. (3).

$$\hat{y} = \arg min_{y=1,2} \sum_{k=1}^{2} P(k|x) C(y|k), \tag{3}$$

where C is the cost function, $\hat{y}$ is the assigned class of the sample and k is its true class. If a testing sample is classified falsely, then the cost function is equal to 1, otherwise it is equal to 0. This cost function results in the maximum a posteriori (MAP) decision rule, hence each sample is assigned to the class providing the maximum posterior probability for that sample.

The binary $\hat{y}$ output of the classifier is used to calculate the accuracy of the training data obtained using the BCI offline sessions explained in the next session, where the posterior probability values are calculated using Eqns. (4) and (5), are used as continuous-valued outputs and used to control the velocity of the robot.

$$P(x|k) = \frac{1}{(2\pi|\Sigma_k|)^{1/2}} exp\left(-\frac{1}{2}(x-\mu_k)\Sigma_k^{-1}(x-\mu_k)^T\right) \tag{4}$$

$$P(k|x) = \frac{P(x|k)P(k)}{P(x)} \tag{5}$$

C. Offline Session

For the training of the BCI system, subjects first undergo cue-based synchronous offline sessions in which they perform imaginary movements and the system tries to recognize patterns from their EEG signals. While subjects sit quietly during data collection, without visible arm movements, their task is to relax or imagine right arm movements. A trial consists of a passive period followed by a cue period. At the beginning of a trial, a cross '+' is displayed for 3 seconds which indicates a rest period and then an acoustic stimulus indicates the beginning of a cue. Then, a right arrow or 'Relax' text appears as a cue for 6 seconds. Therefore, the length of a trial is 9 seconds as shown in Figure 2. The right arrow cue indicates right imaginary arm movements and the 'Relax' cue orders the subject to relax (see Figure 3). The order of the cues is random and an experiment consists of 5 runs with 40 trials (20 trials for imagery right movement and 20 trials for rest).

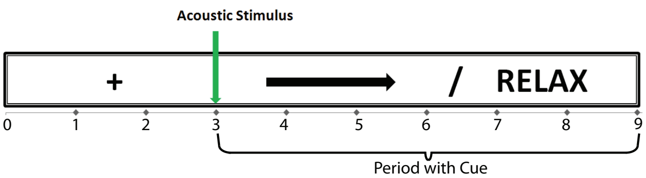

Fig. 2. Timing scheme

Fig. 3. Interface used for the offline sessions

The performance of the classifier is measured by applying two-fold cross validation for 300 times to obtain different training and test datasets consisting of the 75% and the 25% of the entire data, respectively. Overall classification accuracy is obtained by averaging over these 300 classification experiments. 9 healthy subjects participated in the offline sessions. Classification accuracy values vary between 84% and 63% across the subjects. The results show that the performance of motor imagery movement based BCIs, depend on the subject, his/her fatigue level and concentration. The level of accuracy we obtain is comparable to results reported in the BCI literature.

D. Online Session

During online session, right arm imagery movements and the posterior probabilities assigned to right arm imagery movement class are considered to control the velocity of the robot. The online session is a self-paced asynchronous system. The task of the subject is to move a green ball, shown in Figure 4, by means of imagery right arm movements. As it is known that the true class is always right arm imagery movement, only true positive (TP) and false negative (FN) right arm imagery movements are analyzed. Therefore, if data are classified as a rest period, than it is a FN decision and the value of the posterior probability assigned to right arm imagery movement class is equal or less than 0.5 where for TP decisions it is equal or greater than 0.5. For that reason, FN posterior probabilities assigned to right arm imagery movement class, are used as a decreasing effect where TP right arm imagery movement posterior probabilities have an increasing effect on the speed of the robot. Moreover, to have smooth movements at the robotic arm, the mean of the posterior probabilities in the temporal window is calculated and fed to the input of the robotic system. A 3-second window is shifted along the data and the classifier produces a posterior probability output for every second using the model built in the offline session.

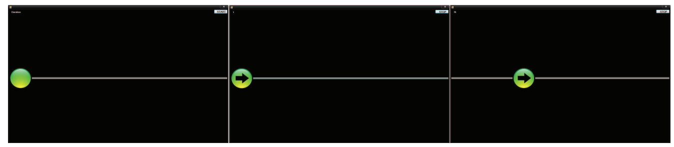

Fig. 4. Interface used for the online sessions

IV. REHABILITATION ROBOT: AssistOn-Mobile

AssistOn-Mobile, a 3 DoF series elastic actuator, is used for assisting patients while completing therapeutic tabletop exercises. AssistOn-Mobile consists of a 3-DoF planar, compliant parallel mechanism coupled to an omni-directional Mecanum-wheeled mobile platform. The deliberate introduction of a multi-DoF compliant element between the mobile multi-DoF actuation unit and the patient transforms the non-backdriveable active holonomic platform into a multi-DoF series elastic actuator. Utilization of series elastic actuation not only eliminates the need for costly force sensors, but also enables implementation of closed loop force control with higher controller gains, providing robustness against imperfections in the power transmission and allowing lower cost drive components to be utilized. Consequently, AssistOn-Mobile is a low-cost active rehabilitation device with an unlimited planar workspace.

In addition to administering active, passive, and resistive therapeutic exercises, AssistOn-Mobile can assist-as-needed [21], that is, it can interactively adjust the amount of assistance, to help increase the training efficiency by ensuring active participation of patients. AssistOn-Mobile can also easily be integrated with BCI using PVFC as detailed in the next section. A picture of AssistOn-Mobile is presented in Figure 5.

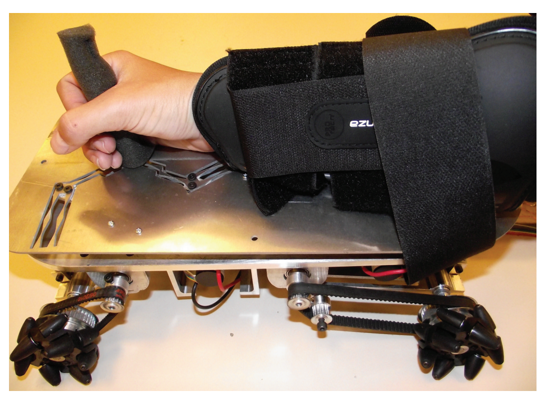

Fig. 5. A prototype of AssistOn-Mobile

V. INTEGRATION OF BCI WITH AssistOn-Mobile

Contour following tasks are preferable in rehabilitation, since these exercises emphasize coordination and synchronization between various DoF during therapeutic exercises, while allowing patients to take control of exact timing along the path. Trajectory following controllers cannot guarantee that patients are always on the pre-determined path due to the radial reduction phenomena [31], [32]. Hence, we utilize PVFC to administer contour following tasks.

Employment of PVFC is advantageous in rehabilitation exercises, since with this controller in place, the task and the speed of the task can be decoupled from each other. Consequently, patients can be allowed to proceed with their preferred pace, while assistance can still be provided as determined by the therapist. In PVFC, the task is embedded in a predefined velocity field, while the speed of the task depends on the instantaneous energy of the closed loop system. In particular, PVFC mimics the dynamics of a flywheel; therefore, it cannot generate energy, but can only store and release the energy supplied to it. As a result, the controller renders the closed-loop system passive *with respect to externally applied forces*. This is one of the unique features of PVFC, as classical passivity-based robot control laws [33]–[35] cannot guarantee passivity when external forces (other than joint motor torques) are considered as the input. Passivity with respect to external forces is crucial in human-machine interaction, since it enhances safety by limiting the amount of energy that can be released to the operator, especially in case of an unexpected system failure.

Let the dynamics of a planar robot system expressed in joint space be given as

$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} = \tau + \tau_e \tag{6}$$

where $M(q)$ and $C(q,\dot{q})$ are inertia and Coriolis matrices, while τ and τ_e are control and external torques applied to the system, respectively. PVFC guarantees passivity of the system with respect to the supply rate $s(\tau_e,\dot{q}) = \tau_e^T\dot{q}$; therefore, external forces satisfy the following passivity condition

$$\int_0^t \tau_e^T\,\dot{q}\,d\tau \geq -c^2 \tag{7}$$

where c is a real number.

In PVFC, the pace of the task is determined by the total energy present in the system. This energy is due to the initial conditions and the work done by the external forces, that is, the energy provided/subtracted by the patient and disturbance forces acting on the system. However, the speed of the contour following task can also be controlled by regulating the total energy of the system by the actuators through an exogenous control term appended to the original PVFC controller. This extra control term features a speed coefficient r that allows easy modification of the task speed. The reader is referred to [36]–[38] for theory and implementation details of PVFC.

For BCI experiments, to enable online adaptation of robot assisted rehabilitation exercises with the intention of the patients, the posterior probabilities extracted from the LDA classifier are used as the continuous-valued outputs to PVFC. These outputs correspond to the instantaneous levels of motor imagery during the movement, and are used to guide the speed of the contour following task by directly adjusting the speed coefficient r in PVFC. With increased level of "intention", a higher speed to complete the task is supplied to the patient providing feedback to encourage active participation of the patient.

VI. EXPERIMENTS

We have performed a feasibility study with a healthy subject for a single session in order to validate the applicability of the proposed control scheme. The experimental setup consists of a Biosemi ActiveTwo EEG System and ASSISTON-MOBILE robot as shown in Figure 6. PVFC is implemented in real-time with a sampling frequency of 500 Hz through a desktop computer equipped with a PCI I/O card.

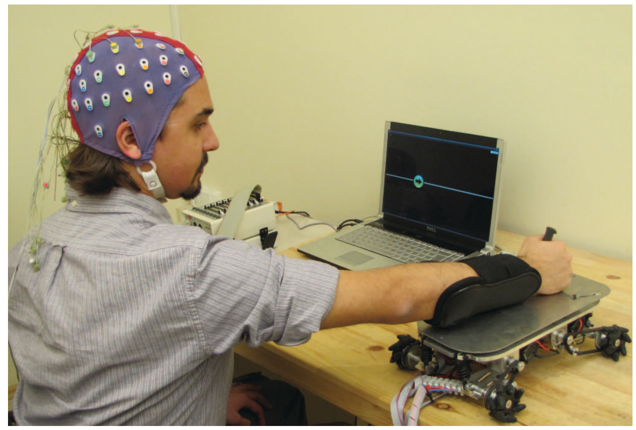

Fig. 6. Experimental setup consisting of the Biosemi ActiveTwo EEG measurement device and ASSISTON-MOBILE

The experiment starts by introducing EEG-based BCI system to volunteers using the test algorithms detailed in Section III. Once the subject is ready, the first phase of the experiment is initiated to familiarize the subject with the online modification of the speed of the contour following task. In this phase, the subject is instructed to control ASSISTON-MOBILE via motor imagery of his/her right arm movements tracing the contour, without causing any actual movement with the arms. At this phase, there is no physical interaction with the robot, but the subject is placed in front of ASSISTON-MOBILE so that he/she can observe the result of the intended movement.

In the second phase, the subject is attached to ASSISTON-MOBILE and asked not to make any voluntary arm movements, while he/she controls the robot via motor imagery of his/her right arm movements tracing the contour using the proposed control framework. In order to avoid sudden variations in the contour tracking speed, instantaneous signals provided by the BCI classifier at each second are averaged over 3 seconds using a moving window for a smoother therapy experience.

This phase of the experiment starts with ASSISTON-MOBILE in idle condition and the user is instructed to imagine moving his/her right arm to follow the desired contour, which is taken as a straight line for simplicity. With increased level of intention, a higher speed to complete the task is supplied to the patient providing positive feedback to encourage the active participation of the patient. Once the contour is traversed in forward direction, motion of the device is deliberately stopped and the subject is instructed to rest for a few seconds. Then, the contour is traversed backwards.

The subject whose offline session data had 72% averaged classification accuracy, participated in the experiment involving control of ASSISTON-MOBILE. Figure 7 depicts a sample plot for the kinetic energy of the system, as well as the windowed

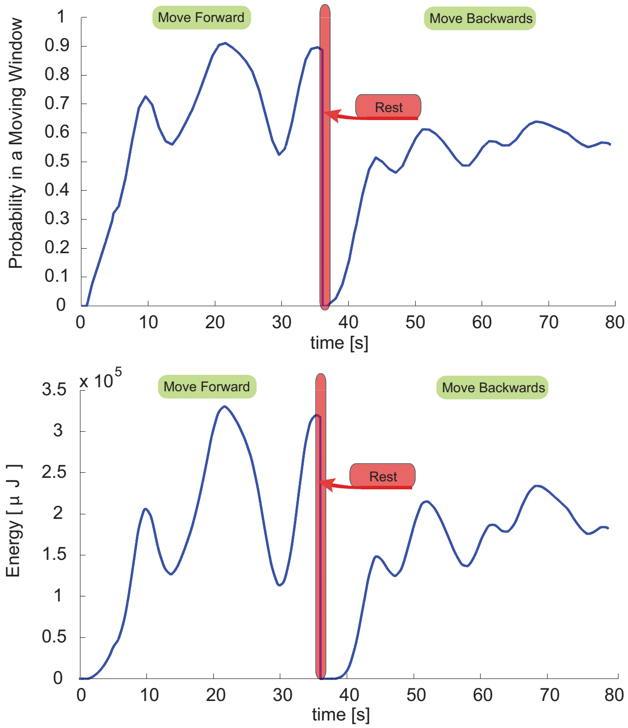

Fig. 7. (a) Moving window averaged probability of patient intention and (b) kinetic energy of the augmented system

probability values provided to PVFC at each second throughout the exercise. As detailed in Section IV, PVFC can regulate the speed of the contour tracking task by providing/extracting energy to/from the system through its control parameters depending on the intention level of subjects. Therefore, kinetic energy of the overall system presented in Figure 7(a) is directly proportional to the tracking speed in the given desired velocity field [39]. Comparing Figure 7(a) and (b), it can be observed that PVFC can successfully administer the contour following task at the speed levels dictated by the BCI signals.

Figure 8 presents the magnitude of the resultant interaction forces between the subject and ASSISTON-MOBILE during the same trial. During a large portion of the exercise, subject applies no apparent external forces, while some unintentional movements can be observed at several instances. Note that residual movements, such as involuntary contractions, can also be applied by patients on the device. Thanks to inherent passivity of our contour tracking controller with respect to external forces, the coupled human-robot system stays passive and faithfully tracks the desired contour even under such forces.

VII. CONCLUSIONS

In this study, we have proposed and implemented a BCI-based robotic rehabilitation system that enables online modification/adaptation of exercises with the intention of patients. In our experiments, the subjects first underwent cue-based synchronous offline sessions and were asked to rest or imagine to move their right arm, according to the random cues shown in the BCI system. LDA algorithm was used to classify ERD/ERS patterns of their EEG signals as "move" or "rest". This binary classification output was used to compute the accuracy of the classification and accuracy levels were found to be in line with the state-of-the-art. Afterwards, for the self-paced asynchronous online sessions, the subjects were asked to only imagine right arm movements. Instead of using binary classification output, the implicative probabilities of intention extracted from the LDA classifier were directly used as the continuous-valued outputs to control the speed regulation of contour tracking tasks, so that patients actively participate in therapies. The control scheme was successfully implemented on a holonomic mobile platform, ASSISTON-MOBILE, where the pace of contour tracking was increased with increased intention level classified by BCI. Feasibility studies with healthy subjects have been completed, where subjects were asked to imagine the movement with no arm movement and with arm movement assisted by ASSISTON-MOBILE. Since these experiments were primarily designed for patients with little to no motion capability, increased intention to move the injured limb was rewarded by faster task execution. On the contrary, lower intention levels were penalized by slowing down the movement and halting it at the worst case. The proposed framework with contour tracking exercises has been shown to enable seamless on-line modification of task speed without endangering the safety of the patient, especially due to externally applied forces.

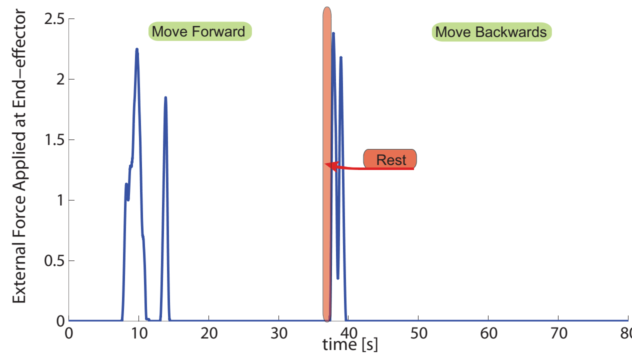

Fig. 8. Force Readings during the Exercise

Future work includes the comparison of the instantaneous intention levels of motor imagery during the movement between the posterior probabilities obtained from the EEG data and electromyography (EMG) signals. Moreover, a larger scale experiment with healthy volunteers and clinical trials with stroke patients are planned to further test efficacy and effectiveness of the proposed approach.

VIII. ACKNOWLEDGMENT

This work was partially supported by Sabanci University under Grand IACF-11-00889, and by the Scientific and Technological Research Council of Turkey under Grants 11E056 and 111M186.

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