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Augmenting Cognitive Processes in Robot-Assisted Motor Rehabilitation

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***Abstract*— Cognitive processes, such as motor intention, attention, and higher level motivational states are important factors that govern motor performance and learning. Current robot-assisted rehabilitative programs focus only on the physical aspects of training. In this paper, we propose a framework for motor rehabilitation based on the augmentation of cognitive channels of patient-robot interactions and using it to deliver a more optimal therapy. By examining the cognitive processes involved in motor control and adaptation, it is argued that optimal therapy needs to be considered in the context of a complete motor scheme consisting not only of sensorimotor signals, but also their interactions with cognitive operations, such as motor planning, attention, and motivation, which mediate motor learning. We outline a few BCI-based modules for the detection and monitoring of relevant cognitive processes, which provide inputs for the robot to automatically modulate parameters of the rehabilitation protocol. Preliminary investigations on a BCI module for detection of motor intention, performed on a small group of stroke patients, show feasible accuracies.**

I. INTRODUCTION

Recent statistics identified stroke as a leading cause of death in the world. Yet, the consequences of stroke spread beyond patient mortality. Of those who survive a stroke, at least 30% fail to make a complete recovery and will experience disabilities relating to movement, speech, concentration, and cognition, and a further 20% will continue to require long-term care for activities of daily living [1].

The principles guiding post-stroke motor rehabilitation are mainly founded on neuro-plasticity, which refers to the experience-mediated functional reorganization of the brain. In particular, it is posited that the functional roles of the affected tissue are adopted by parallel brain regions in the unaffected hemisphere, facilitated by descending brain fibers from one brain hemisphere that do not cross over to the contralateral body hemisphere [2]. Evidence from animal studies suggest that the environment has an effect on the post-stroke reorganization of undamaged cortical tissues in primates [3], alluding to the possible role of exercise in the motor restoration of the paretic limb.

Traditional physical and occupational therapy for stroke patients, such as the Bobath approach and the Motor Relearning Program, typically involve exercises that attempt to overcome motor deficits and improve motor patterns, with the help of therapists [4]. More recently, promising results has been demonstrated in Constraint-induced Movement Therapy, which forces the use of the affected side by restraining the unaffected side [5].

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Although the above rehabilitation methods are well-established in practice, and well-supported by evidence of improved outcome, they are labor intensive and expensive. Furthermore, manually assisted movement training lacks repeatability and objective measures of patient performance and therapy progress. With the advent of robotic technology and new insights in the neuroscience of human motor adaptation, there is a paradigm shift to robot-assisted motor rehabilitation [6]. Rehabilitation programs that incorporate robotic and information technology can ameliorate the increasing burden on manpower by automating parts of the process that are repetitive and time-consuming. Additionally, robots are able to provide consistent training in an efficient manner, pervasive and accurate monitoring of the progress of patients. Rich data on body kinematics and dynamics can facilitate analysis on patient condition and shed light on better ways to customize the therapy. Clinical studies have reported significant improvements on rehabilitation outcome based on clinical measures [7], [8].

Most of the current robotic rehabilitation approaches are centered on physical therapy, and devote minimal emphasis to cognitive factors that play a role in determining rehabilitation progress and outcome. For optimal therapy, motor output cannot be considered in isolation. A complete motor scheme consists of interactions between motor planning, execution, sensory feedback, and attention, which in turn mediate motor learning. On top of that, higher level cognitive factors such as motivation and emotion are also determinants of rehabilitation outcome. We propose a new approach of robot-assisted motor rehabilitation which takes into account cognitive processes that play key roles in motor control and learning. State of the art brain-computer interface technology is a fertile ground for research in detecting and monitoring cognitive processes such as intention, attention and emotion. The research provides a novel dimension towards the goal of optimizing motor therapy that can potentially enlarge the group of patients who can benefit from robotic rehabilitation.

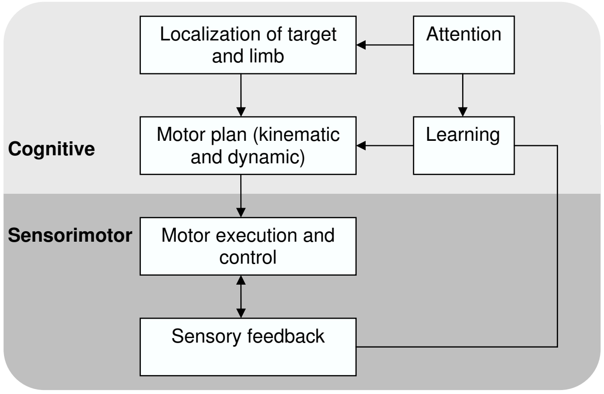

Fig. 1. A complete motor scheme consists of interactions between motor planning, execution, sensory feedback, and attention, which in turn mediate motor learning.

II. MOTOR CONTROL, LEARNING, AND THE COGNITIVE PROCESSES INVOLVED

Figure 1 provides a conceptual framework that illustrates the putative roles and relationships between motor intention/planning, execution, and modulation of sensory activities by attention during a complete motor scheme for goal-directed reaching movements. First, localization of target and limb takes place, where the Central Nervous System (CNS) resolves the target-centered coordinates, limb-centered coordinates and eye-centered coordinates into a common frame of reference in order to determine the true spatial relationship between the target and limb relevant to the reaching task. This is followed by the computation of the direction and extent of the error in limb location relative to the target, which is key to the planning of movement kinematics, that is, the specification of the path and speed of movement. Based on the planned kinematics, the CNS specifies the feedforward motor command, which constitute the forces needed to be produced to move the limb against its own inertia as well as any external forces, via an inverse dynamics map [9].

With the planned movement dynamics, the motor circuits residing at the spinal cord level then coordinate the temporal aspects of muscle force generation needed to generate the actual movement. During the movement, the error kinematics of the limb relative to the target are monitored via visual and proprioceptive pathways, with the help of forward models that predict future limb states based on an efference of the motor command [10]. Then, feedback control via reflexes and intrinsic viscoelastic muscle properties takes place to stabilize the limb against unexpected perturbations.

Motor learning involves the adaptation of the inverse dynamics map which generates motor commands in response to a novel motor task or interaction with the environment. Humans form appropriate internal models to overcome external dynamics in both stable [11], [12] and unstable interactions [13], [14], and recent results suggest that these seemingly different strategies for learning can be unified under a framework which concurrently minimizes neural feedback, in the form of reflexes, and muscle activation [15].

Motor intention can be understood as a collection of cognitive processes that initiates a goal-directed sequence of body movements. In particular, it encompasses the localization of target and limb, as well as the planning of movement kinematics and dynamics. An important cognitive precursor to any attempt to generate, or imagine, a movement in space is visuo-spatial attention to limb and target positions. During motor execution, attention to task related features of the movement has an effect on motor performance [16], [17]. These may be kinematic features related to position error and sensorimotor transformation, or dynamic ones related to force production. Evidence from a neuroimaging study [18] suggests that visual attention during movement modifies brain activity in ways that are different from those occurring for movement or visual attention alone.

The roles of attention in the learning of novel sensorimotor transformation, and in the adaptation to novel force perturbations, have been investigated in several studies. When cognitive load is imposed on a prism adaptation task, subjects showed increased terminal pointing errors [19]. Furthermore, it was found that divided attention impairs motor adaptation to a significantly greater extent than motor control [16], [20], and that attention is necessary to monitor movements and evaluate errors when learning to perform a novel motor task or in the presence of motor deficit [21].

In summary, intention and attention are indispensable to the voluntary initiation of movements and have significant effects on motor and learning performance. The implication for post-stroke motor rehabilitation is that the focus on only the explicit behavioral aspects, such as limb displacements, while ignoring the internal cognitive processes that underlie movement generation and adaptation, may lead to suboptimal or incomplete learning of motor scheme for unassisted activities of daily living.

III. AUGMENTING COGNITIVE PROCESSES IN MOTOR REHABILITATION

In current works on robotic rehabilitation, the robot provides assistive actions based solely on the motor output variables such as limb velocity or electromyogram (EMG) signals, but not the cognitive processes that drive and monitor voluntary movements. The assumption is that the patient is well motivated towards the therapy and fully utilizing the neural mechanisms pertaining to motor intention and attention. For typical robot-aided rehabilitation involving reaching movements of the paretic limb, in the absence of any motor output from the patient within a time limit, the robot automatically moves the patient's limb to the target and back. In this case, it is difficult to judge objectively whether the patient is cognitively involved in the process. Did the patient generate a motor plan to reach the target even though the movement was not initiated, or attend to sensory feedback when the movement is passively performed with the help of the robot? Current approaches do not readily lend themselves to addressing these pertinent questions.

For a more holistic approach, we propose the augmentation of non-invasive brain-computer interfaces (BCI) technology to robot-assisted rehabilitation to allow relevant cognitive

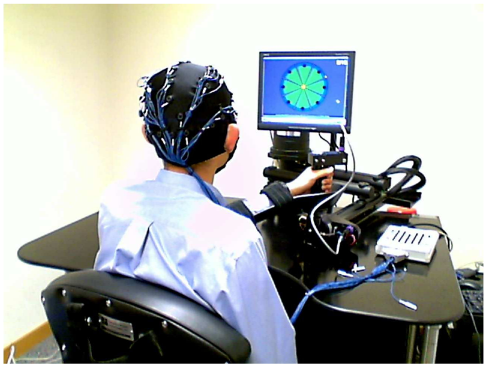

Fig. 2. BCI-based robotic rehabilitation system: Augmenting cognitive processes such as intention, attention and emotion, provide a novel dimension towards the optimization of motor therapy.

processes to be detected and monitored. This is motivated by the recent advent of BCI technology that enables the translation of thoughts and intents of humans to actions by machines (for instance, a wheelchair [22]), as well as monitoring and analysis of cognitive processes. Among the few non-invasive techniques for brain signal acquisition, including functional magnetic resonance imaging (fMRI), magnetoencephalogram (MEG), near infrared spectroscopy (NIRS) and electroencephalography (EEG), the latter has excellent temporal resolution, and is considered the best choice for BCI in affordable biofeedback and rehabilitation practices. In the remainder of this section, we describe specific BCI-based modules for the detection and monitoring motor intention, attention to sensory stimuli, as well as motivation and engagement. Based on these information, the robot can automatically modulate parameters of the rehabilitation protocol, e.g. speed, intensity and resistance, so as to achieve more optimal therapy.

A. *Motor Intention*

Motor intention, in the context of normal subjects, is the mental representation of the cognitive operations that initiate volitional movement. However, given the fact that stroke patients may be unable to initiate movements with their affected limb, it is not apparent how motor intention for stroke patients can be characterized. Motor imagery is the cognitive process during which the representation of a movement is internally reproduced in the absence of any motor output. It has been postulated that similar neural mechanisms underlie both motor imagery and motor planning [23], and that the two processes are different only in the sense that the motor execution is inhibited along corticospinal pathways in the former case [24]. This implies that motor intention can be detected through motor imagery, with the caveat that the latter mechanisms are intact. Even if they are not intact, it can be hypothesized that neuroplasticity is a viable mechanism for driving the functional reorganization that ultimately restores internal representations related to motor imagery.

Detection of motor imagery with BCI has been investigated with some success. Several EEG studies show that motor imagery activates primary sensorimotor areas, and give rise to distinct mental processes related to movement known as Event-Related Desynchronization (ERD) / Synchronization (ERS) for different frequency bands. In particular, imagination of hand movement results in ERD of contralateral hand area in the cortex [25]. To detect motor imagery for a specific action, one can employ the approach of model training and pattern classification. The acquired EEG data can be analyzed in the temporal-spatial domain, followed by the construction of optimal spatial filters that facilitates the discrimination of the different classes of EEG measurements (e.g. left and right movements) via a classifier.

Based on this information, in the context of goal-directed reaching movement, the robot will only be activated to move the patient's paretic limb to the target if the BCI module detects motor intention. It is well known from sports psychology research that mental rehearsal of movements helps to keep the motor program active, improve future performance of the task, and facilitate the learning of new motor behavior [26]. We postulate that with the added BCI mechanism which ensures the patient's cognitive involvement through active motor imagery, similar benefits can be gained in motor rehabilitation. Additionally, it is possible that BCI-based rehabilitation robot can help to restore brain representations of motor imagery damaged by stroke. BCI enables a new pathway in which motor imagery is mapped to robot actions that drive patient limb movements. The elicited 'motor output', in turn, cues sensory feedback, along visual and proprioceptive channels, that mediates brain networks involved in producing the motor imagery. By ensuring that the elicited 'motor output', with respect to a particular task, is consistent and repetitive, we can create conditions in which the restitution of neural representations of motor imagery, for that task, can take place, possible at an accelerated rate.

B. *Attention to Sensory Stimuli*

While an intensive, highly repetitive, and task-oriented sensorimotor therapy is linked to the induction of long-term brain plasticity and improvement of functional outcome, it is also possible that repeated and unchallenging stimuli from highly practiced movements can diminish attention to sensory information in the motor control loop. This is a possible scenario in robotic rehabilitation programs where the robot moves the patient's limb to the various targets in a highly repetitive fashion over a large number of trials, inducing factors that lead to lapse of attention in the patient.

Evidence show that diminished attention to motor task impedes the motor learning process significantly, although the effect on feedback control of movements is less dramatic [20]. Interestingly, it has been found that the capacity of sustaining attention plays an important role in motor recovery following stroke [27]. Notable correlation was found between sustained attention capacity at 2 months and motor function after 2 years [28].

Visuo-spatial attention can be detected with a BCI module by examining event-related potentials (ERPs), where an increase in early sensory potentials (P1 component), elicited by a cued target relative to an uncued one, indicated that the cues target is being attended to [29]. Besides ERPs, the spectral content of the EEG activity, particularly the gamma band with frequencies greater than 30 Hz, can also be analyzed to determine if attention is present [30]. For discrimination of voluntary and involuntary attention, it appears that only gamma-band analysis, and not ERP analysis, is able to show differences between the two classes of attention [31].

The implication here for robotic rehabilitation systems is that motor relearning can be made more optimal by establishing a way to measure the patient's attention during the motor task, and then modulating feedback to the patient in ways that increase attention to relevant features of the task. For example, upon detection of attention lapse, the training can be punctuated with various forms of feedback such as auditory alerts, visual stimuli, force perturbations, or a multimodal combination of these interactions that recapture attention of the patient to the motor task.

C. Motivation and Engagement

At higher centers of the brain, there are cognitive factors shaped by motivational and emotional state of the patient, and these are believed to play a role in the recovery process. Reports have indicated that post-stroke depression has a high incidence of more than 60% [32], and that depression has an effect on the functional outcome of a stroke [33]. It is widely accepted among clinical professionals that the concept of motivation is an important determinant of motor recovery, as supported by empirical studies [34], [35]. Motivation is in turn mediated by personality and social factors [36], thus lending support to the use of socially assistive robotics for stroke rehabilitation [37], and the enhancement of the gaming aspects of rehabilitation [38].

Results from a study on neuroplasticity [39] has shed some light on the theory that motor skill acquisition, rather than repetitive use, is the key driver for reorganization of sensorimotor maps in the cortex. Specifically, it was shown that if animals are trained on a skill-demanding task that requires motor learning results in various changes in neuronal morphology corresponding to gradual improvement in performance on the task. Conversely, no changes in motor maps or neuronal morphology were observed if the task required little or no learning. Assuming that the animal model is valid, an important implication for stroke rehabilitation is that repetitive practice alone is not sufficient. As motor skill improves, there is a need to introduce additional task demands so as to continually motivate the patient to be cognitively involved in solving the problem, thereby engaging the mechanisms of learning that drive the reorganization of damaged pathways and maps in the brain.

There is a fine balance between a rehabilitation program that is under-stimulating and one that is exceedingly difficult to the extent of creating undue stress for the patient. Current approaches that tailor the adaptive therapy only to changes in behavioral measures of motor skills may not capture all the facets of an optimal therapy. The same external measures of motor performance may not provide any indication of the degree of cognitive effort or the level of psychological stress

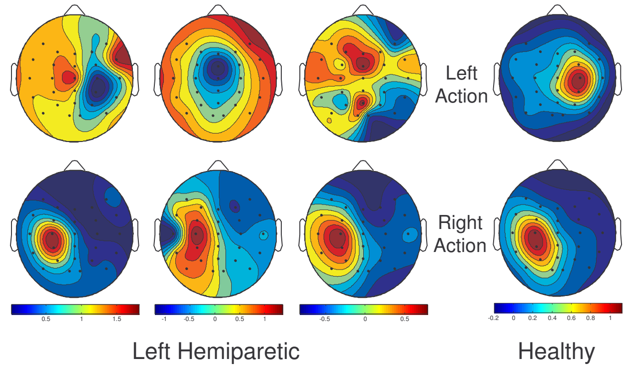

Fig. 3. Representative spatial patterns of healthy and left hemiparetic subjects who performed right hand tapping and left hand motor imagery. Right action is correlated with activity in the left hemisphere for both healthy subjects and patients. However, activity correlated with left action is not in the right hemisphere for two of the patients (second and third from left).

in the patient. Furthermore, the perception of task difficulty and self-evaluation of progress is expected to vary across patients in view of individual factors that include attitude, self-motivation, and personality. Based on the hypothesis that motivational and emotional factors influence outcome of therapy, it makes sense to extract and translate these features to appropriate actions by the robot.

We propose to employ BCI techniques for the detection and monitoring of neurophysiological measures of emotional and affective states, which can be combined with behavioral measures of motor skills and then mapped to an appropriate strategy that adapts the level of difficulty of the motor task according to the high level cognitive processes. As a precursor to emotion recognition, we have developed a method for autonomous detection of emotional response associated with facial expressions, based on spectral-spatial features extracted from EEG. Divide-and-conquer classification of 6 facial expressions, with 10x10-fold cross-validation, yielded a mean accuracy of 87.1% for 4 subjects [40].

IV. PILOT STUDY ON MOTOR INTENTION

In this section, we present the results of a pilot study on the integration of cognitive module detecting movement intention into the robotic rehabilitation protocol. The intention detection module serves as a gate for activating the robot to provide assistance of movement. This minimizes the likelihood of the scenario of passive rehabilitation consisting largely of movements performed solely by the robot, without any mental effort on the part of the patient. Such a module will comprise 2 phases: offline calibration and online therapy. The calibration phase trains a model for classifying movement intention, based on supervised learning on labeled data. The online phase then relies on this model for detecting movement intention during real interactions with the robot.

The data in this study was collected, with approval from the Ethics Approval Board, from a group of healthy subjects and hemiparetic stroke patients. EEG was measured using a NuAmps amplifier (Compumedics), low pass filtered with a cutoff frequency of 40Hz, and sampled at 250Hz. We used 25 recording electrodes covering the frontal, motor, and parietal areas, with ∼2.5cm inter-electrode spacing. In addition, a reference electrode was attached to the nose, and the ground was ∼2.5cm anterior of Fz. Impedance of the electrodes was below 10$k\Omega$. No artifact removal is performed.

To extract relevant features from EEG, we employ the Filter Bank Common Spatial Pattern algorithm (FBCSP), which has been shown to be effective for motor imagery tasks [41]. The FBCSP computes, within each of several selected frequency bands, features with variances that are optimal for discriminating between two classes of data. For illustrative purpose, figure 3 shows representative spatial patterns from a healthy subject who performed finger tapping on both hands, together with three left hemiparetic stroke patients who performed right hand tapping and left hand motor imagery. Details of the study is found in [41]. For right action, spatial patterns are seen over the left hemisphere for both healthy subjects and patients. However, for left action, the spatial patterns observed are very different from those for right action. While the spatial patterns for the healthy subject are on the right hemisphere, those for the patients are not localized in the same region, possibly because the brain sites responsible for generating ERD/ERS during left hand motor imagery are damaged by stroke. We are launching further investigations on correlating the spatial patterns with neurological damage revealed by magnetic resonance imaging. Nevertheless, the different spatial patterns across the two types of actions, as elicited by FBCSP, provide important features to discriminate one class from the other.

The actual experiment, which is implemented on the MIT-Manus robot, is concerned with detecting EEG correlates of movement intention. Patients were instructed to perform motor imagery on the affected arm, while healthy subjects can do it on either arm. Each subject rested his/her arm on the robotic device and faced a computer screen, which displayed visual cues instructing the subjects to perform or cease motor imagery. Each trial comprised EEG data segment recorded from 0.5s to 2.5s after the visual cue.

In the calibration phase, each subject performed a balanced set of 80 trials with and without motor imagery, presented in random order. On trials involving motor imagery, at 3s after the onset of the visual cue, the robot moved the arm to one of several targets on the horizontal plane, and then returned to the original position. It remained motionless on trials not involving motor imagery. In the online testing phase, each subject performed a balanced set of 40 trials. During each trial, the post-cue EEG data segment is autonomously analyzed. After relevant features have been extracted from EEG using the FBCSP algorithm, the Naïve Bayes Parzen Window classifier is used to detect motor imagery. Only when motor imagery is detected does the robot execute the motion. For stroke patients, a second session was conducted on a separate day.

Table I and II show the detection accuracy for healthy subjects and patients. For both groups, the calibration accuracy is higher than the online accuracy, with p-value$<$0.05 based on paired-sample t-test. This is possibly due to overtraining in the calibration dataset, which weakens the generalizability of the model to unseen data during online testing and/or non-stationarity of EEG across the different conditions of calibration and online testing. Nevertheless, the online accuracies for both groups, at about 75%, are significantly above chance. Between the groups, the mean online accuracies are comparable, suggesting that neurological damage in the hemiparetic stroke patients does not significantly affect their capability of operating a BCI-controlled robot compared with healthy subjects. For stroke patients, the online accuracies between the 2 sessions are statistically insignificant (p-value=0.606).

TABLE I
ACCURACY OF DETECTION FOR HEALTHY SUBJECTS

Healthy Subject	**H1**	**H2**	**H3**	**H4**	**mean ± s.t.d.**
Calibration Accuracy %	94.4	90.6	95.0	88.2	92.0 ± 3.2
Online Accuracy %	85.0	72.5	67.5	75.0	75.0 ± 7.4

TABLE II
ACCURACY OF DETECTION FOR STROKE PATIENTS

Patient	**P1**	**P2**	**P3**	**P4**	**mean ± s.t.d.**
Calibration Accuracy %					
Session 1	92.5	90.6	93.1	83.8	90.0 ± 4.3
Session 2	82.5	94.4	93.1	84.4	88.6 ± 6.0
Online Accuracy %					
Session 1	82.5	82.5	67.5	72.5	76.3 ± 7.5
Session 2	80.0	75.0	75.0	70.0	75.0 ± 4.1

V. CONCLUSIONS

This paper has presented a framework for motor rehabilitation by augmenting cognitive channels of interactions between patient and robot. These cognitive processes play fundamental roles in motor performance and skill acquisition, and need to be taken into consideration for optimal therapy. By providing communication between the patient's mental processes and the robotic system through BCI technology, the functional outcome of rehabilitation is expected to improve. Additionally, they provide key evaluative measures that facilitate customization of rehabilitation strategies by human therapists. Preliminary results on BCI detection of movement intention, for a small group of stroke patients, show feasible accuracies under online operation. Based on the promising results of this pilot study, we are currently clinical studies on the treatment effect of our BCI-robotics based neurorehabilitation for a larger group of stroke patients. Future topics of investigation include detection of attention to movements, as well as motivational and emotional states of the patient.

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