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A Pre-Clinical Framework for Neural Control of a Therapeutic Upper-Limb Exoskeleton

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Abstract

In this paper, we summarize a novel approach to robotic rehabilitation that capitalizes on the benefits of patient intent and real-time assessment of impairment. Specifically, an upper-limb, physical human-robot interface (the MAHI EXO-II robotic exoskeleton) is augmented with a non-invasive brain-machine interface (BMI) to include the patient in the control loop, thereby making the therapy 'active' and engaging patients across a broad spectrum of impairment severity in the rehabilitation tasks. Robotic measures of motor impairment are derived from real-time sensor data from the MAHI EXO-II and the BMI. These measures can be validated through correlation with widely used clinical measures and used to drive patient-specific therapy sessions adapted to the capabilities of the individual, with the MAHI EXO-II providing assistance or challenging the participant as appropriate to maximize rehabilitation outcomes. This approach to robotic rehabilitation takes a step towards the seamless integration of BMIs and intelligent exoskeletons to create systems that can monitor and interface with brain activity and movement. Such systems will enable more focused study of various issues in development of devices and rehabilitation strategies, including interpretation of measurement data from a variety of sources, exploration of hypotheses regarding large scale brain function during robotic rehabilitation, and optimization of device design and training programs for restoring upper limb function after stroke.

I. INTRODUCTION

Stroke is the leading cause of neurological disability in the United States [22]. Repetitive, task-specific training of the affected limb can result in significant motor recovery more than one year after the stroke incident [21]. Experiments show that robot-assisted training of the impaired arm can be as effective as unassisted repeated practice [14] and more effective than neuro-developmental therapy commonly used for motor recovery after stroke [19]. Furthermore, robotic rehabilitation systems offer increased efficiency, lower cost, and new sensing capabilities to the therapist.

Given the proven potential of robotic rehabilitation systems, we aim to accelerate the development, efficacy, and use of robotic rehabilitation after stroke. This paper presents our approach to the development of robotic rehabilitation systems designed to capitalize on the benefits of patient intent and real-time assessment of impairment. We use a brain-machine interface (BMI) based on electroencephalography (EEG) to control a robotic exoskeleton that will guide a patient's limb through a naturalistic movement with the goal of training brain networks that might aid in motor recovery from incomplete paralysis. The robotic device enables accurate positioning of the impaired limb while simultaneously providing assistance or resistance forces and collection of motion data that can be used to characterize the quality of the patient's movements. To evaluate the efficacy of the system and the degree of motor recovery, we use real-time data acquired from the robotic exoskeleton and the BMI to calculate objective performance metrics, and we compare these to traditional clinical measures of motor function.

II. BACKGROUND AND MOTIVATION

A. Robotic rehabilitation systems

Various aspects of robotic rehabilitation have been investigated previously, including a significant effort in the design of novel rehabilitation robots (e.g., [10], [13], [16]). Rehabilitation engineering research has increasingly focused on quantitative evaluation of residual motor abilities in an effort to obtain an objective evaluation of rehabilitation effects [6]. Exoskeleton rehabilitation robots, such as the MAHI EXO-II (Fig. 1) used in our system [9], [18], offer the advantage of precisely recording and monitoring isolated joint movements of the arm and wrist, rather than just the end effector (as in the MIT-MANUS and MIME systems [13]), and hence are better-suited for quantifying motor impairment of multi-joint upper extremity reaching movements.

B. Neural interfaces

The last decade has seen remarkable advances in neural decoding and assistive BMI systems to reconstitute motor function, enabling control of computer cursors, robotic limbs, and orthoses in real time (e.g., [2], [4], [11], [20]). Based on recent findings that BMI training can be used for selective induction of use-dependent CNS plasticity that might facilitate motor recovery, the concept of restorative BMI has emerged [3], [5], [7]. Although long-term BMI use has been shown to result in the formation of a stable, addressable, and robust cortical map for 2D prosthetic control [8], little is known about the nature of the cortical representation for BMI control of limb movements at the macro-scale of EEG. We believe that developing non-invasive BMI-exoskeleton robot systems in closed-loop with the injured brain is critical for (1) understanding current limitations of BMI systems, (2) improving their chance to succeed when applied to patient populations such as stroke, (3) allowing robots to work cooperatively (i.e., shared-control) with people to extend, restore, or augment their human capacities, and (4) conducting reverse-translational studies of the effects of BMI-induced cortical plasticity that can contribute to a better understanding of cortical physiology while informing computational models of brain function.

C. Assessing motor deficits and recovery after stroke

Clinical measures of motor improvement, while reliable and widely accepted, have several drawbacks including variability, subjectivity, and lengthy evaluation procedures [12], [17]. In contrast, robotic measures (e.g., movement accuracy, timing, and smoothness) and EEG-based measures have the benefits of being completely objective, capturing quality of movement and the current state of the movement representation, and providing patients and therapists with immediate feedback on patient progress. Despite these advantages, robotic and EEG-based measures lack the wide acceptance of clinical measures because they are often device- or task-specific and have not been tested for relevance to clinical outcomes. Our system will record robotic and EEG-based measures during clinical testing to facilitate the identification of task- and device-independent robotic and neurophysiological measures that correlate well with clinical measures, enabling the incorporation of objective measures of motor function into clinical rehabilitation procedures.

III. APPROACH

The goal of this research is to accelerate the development, efficacy, and use of robotic rehabilitation after stroke by capitalizing on the benefits of patient intent and real-time assessment of impairment. Toward this goal, we augment the MAHI EXO-II, a physical human-robot interface, with a non-invasive EEG-based BMI to include the patient in the control loop and make the therapy ‘active’. Using this system, we are developing robotic and EEG-based measures of motor impairment and recovery that will allow real-time evaluation of patient progress and drive patient-specific therapy sessions. When appropriate, the MAHI EXO-II can then provide assistance or challenge the participant as needed to maximize rehabilitation outcomes. The following sections describe the components of the system and the methods for evaluation.

A. The MAHI EXO-II robot exoskeleton

The MAHI EXO-II (Fig. 1) is a five-DOF exoskeleton comprised of a revolute joint at the elbow, a revolute joint for forearm rotation, and a 3-RPS (revolute-prismatic-spherical) serial-in-parallel wrist actuated by DC brush motors for lowered cost. The design allows for 100% of wrist abduction/adduction range-of-motion (ROM) and 63% of wrist flexion/extension ROM during activities of daily living (ADL), and offers key design improvements over prior versions such as reduced backlash and singularities, increased torque output in some DOF, improved wearability by allowing the device mount to be abducted at the shoulder, and streamlined interchange between left and right arm configurations [15]. The device is equipped with high-resolution sensors that enable accurate measurement of position and velocity in the workspace (see [9], [10] for detailed performance data). During therapy, the device actuators can provide variable and patient-controlled assistance forces to vary the difficulty of the task.

B. The non-invasive BMI-exoskeleton system

A closed-loop real-time BMI system will be integrated with the physical exoskeleton and a real-time open source virtual exoskeleton model (VEM), as shown in Fig. 2. Our architecture modularizes the key components of the neural exoskeleton system into inputs, signal analysis, controls, plant, and presentation (virtual or physical). As a result of the common interfaces of the system, EEG decode algorithms implemented in the signal processing module can be used interchangeably, which facilitates comparison across labs and teams. In Fig. 2, the Inputs correspond to the EEG signals (outputs of Block II) recorded using a 64 channel Active electrode EEG cap (Block I). Block III corresponds to the Signal Analysis, which consists of our proposed time-domain decoding algorithms, including sub-band filtering and subsystems for decision fusion. The Controls and Plant are embedded within Block IV, which represents the virtual or actual MAHI EXO-II. To harness the increased sensing capabilities in advanced exoskeleton device designs, users will require interfaces supported by novel forms of sensory feedback and novel control paradigms. To allow for this, Block V contains the presentation of visual and 'robotic' feedback of the exoskeleton during BMI operation. The proposed system is the first comprehensive robust, safe, solution based on EEG decoding of natural volitional movement, using state-of-the-art active EEG and a robotic exoskeleton platform for use by human subjects. Note that for improved robust brain control, the system has built-in redundancy due to its multiple decoders (e.g., Wiener and Kalman filters, and a motor intent classifier for switching the neural interface during periods of non-movement intention).

C. EEG Methods

All participants will complete training to learn how to use their intentions to move the exoskeleton through repeated single-joint and multi-joint movements while they wear the BMI system. During BMI training, subjects will imagine moving their limb while watching the robot's resulting movement. (For unimpaired subjects, muscle activity from the limbs will be monitored via electromyography (EMG) to ensure that only 'movement thoughts' are used to control the robot; patients will be asked to actively attempt to perform the movements.) Importantly, the single-joint and multi-joint targeted movements will be self-selected and self-initiated by the subjects. (See [1] for detailed behavioral task and setup.) The aim is for patients to intentionally evoke robotic assitance through the BMI to increase the range of paretic arm movement by controlling the robot to move through a larger range than they can produce on their own. For each group, this is accomplished by reconstructing trajectories of the elbow and wrist joints decoded from EEG to control the MAHI EXO-II in real-time with visual feedback of the robot's movement.

D. Clinical measures

To evaluate patient performance, we are focusing on three common clinical measures: Fugl-Meyer (FM) upper-limb component, Action Research Arm Test (ARAT) and Jebsen-Taylor Hand Function Test (JT). These tests rate motor impairment (FM and ARAT) and functional performance (JT) of motions associated with activities of daily living. The time to complete each task is recorded and compared to normative data for interpretation. Our goal is to obtain robotic measures that correlate well with these clinical measures.

E. Structural and functional neuroimaging measures

To look for evidence of neural plasticity over time, structural and functional fMRI will be performed on a 3T MRI scanner. Subjects will perform a controlled repetitive movement task of the hand during an fMRI blocked design paradigm with four cycles alternating

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between 30 seconds of movement followed by 30 seconds of no movement. After the task fMRI, an additional resting fMRI scan will be done to look at functional connectivity of activated regions. Finally, a 10 minute diffusion-weighted sequence will be done to look at structural connectivity. The structural MRI results will be used to measure damage to brain regions involved in upper extremity movement and will provide an anatomical basis to localize the functional MRI data. The functional MRI results will be used to localize activation in brain regions during upper extremity movement and at rest. The DTI will look at structural connectivity.

We anticipate finding increased activation in the stroke-affected primary cortex (M1), premotor cortex (PMC), supplementary motor area (SMA), and ipsilateral cerebellum. We predict that changes in activation of these specific brain regions will correlate with change in behavioral functions and movement quality. We also predict that improvement in behavioral functions and movement quality will positively correlate with the functional and structural connectivity among specific brain regions.

F. Robotic measures

Robotic measures are calculated by post-processing the data files collected via the robotic exoskeleton while the participant makes point-to-point reaching movements. Measures that capture movement speed (such as movement time and average velocities), accuracy (such as trajectory error and variability), and smoothness of movement (such as jerk and number of zero crossings in the acceleration profile) can be used to quantify motor impairment from robotic sensor data. These robotic measures are derived from known characteristics of healthy human movements for center-out reaching tasks and are normalized for broad applicability across robotic hardware.

Currently, we are exploring the use of trajectory error (TE) and smoothness of movement (SM) measures to objectively evaluate motor function. In healthy human movements, the nominal desired trajectory is a straight line from the last target to the current target. Absolute values of the deviations from this straight line trajectory during the point-to-point movement are summed to obtain the raw TE value, which is then normalized with respect to the number of data points and the distance traveled to create a device-independent measure of accuracy. The SM measure is a correlation coefficient that expresses the correlation between the patient’s speed profile and a speed profile utilizing the minimum jerk principle (an optimally smooth speed profile). The TE and SM measures serve as objective assessments of movement quality; TE evaluates the patients’ performance of tracking straight line target trajectories, while SM compares the speed profile of the patients’ movements with the speed profiles observed in healthy people’s movements. Both measures demonstrate how stroke patients’ movements deviate from healthy people’s movements, and they provide practical, fast, direct, and objective evaluations of movement quality.

G. Statistical analyses

The primary goal of our statistical analyses is to evaluate how well the objective robotic and EEG-based measures reflect the motor improvements captured by accepted clinical measures. To determine treatment effects for the EEG, robotic, and clinical measures, repeated measures ANOVA will be used with repeated measures on test day. We will then use regression analyses to investigate the correlation between clinical, EEG, and robotic measures at different days of treatment. Clinical and robotic measures of motor impairment will be compared for each pair (FM-TE, FM-SM, ARAT-TE, ARAT-SM, JT-TE, and JT-SM) across all participants. Correlations between robotic and clinical measures will be used to evaluate the utility of the set of robotic measures. We expect that the chosen robotic measures (TE and SM) will correlate strongly with the clinical measures, which would indicate that these objective robotic measures could be used in place of the equivalent clinical measures.

IV. CONCLUSION

This paper described a novel approach to robotic rehabilitation using patient intent and real-time assessment of motor function to improve rehabilitation outcomes. This approach will lead to more complete integration of robotic exoskeleton devices and brain interfaces, allowing patients to be more active in their therapy. The use of such an integrated system will also allow more objective and reliable evaluation of patient progress by identifying robotic and EEG-based measures that correlate well with accepted clinical measures. Incorporating these objective measures into patient therapy will enable online evaluation of patient progress, leading to more patient-specific therapy sessions in which assistance or resistance can be provided as needed through the integrated physical system. This research will also result in improvements in the understanding of neuromuscular control of upper extremities and large scale brain function during robotic rehabilitation. These advances will be an important step towards the optimization of device design and training programs for restoring upper limb function after stroke.

Acknowledgments

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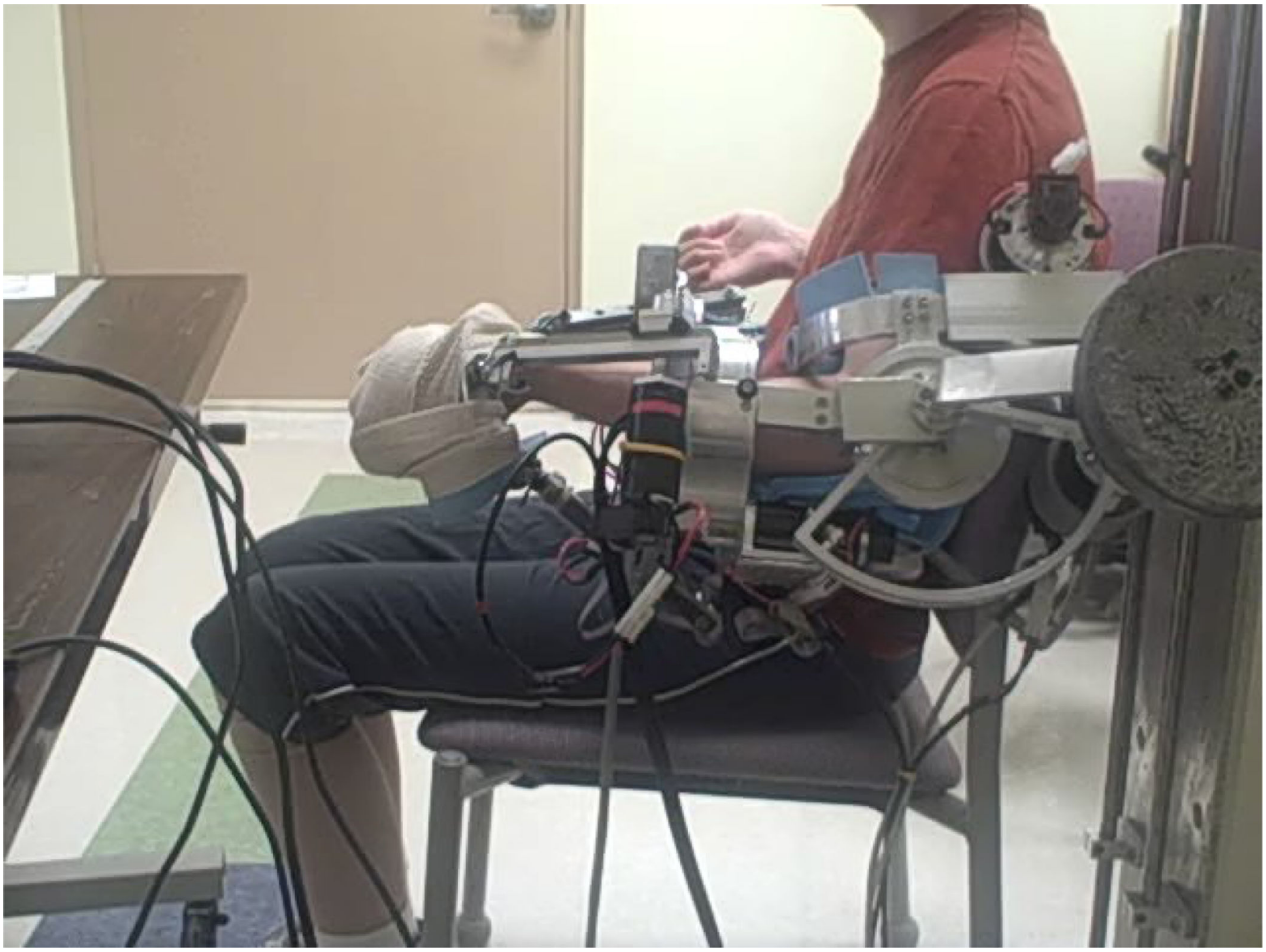

Fig. 1.
MAHI EXO-II exoskeleton on tetraplegic patient, for determination of robotic measures of motor impairment.

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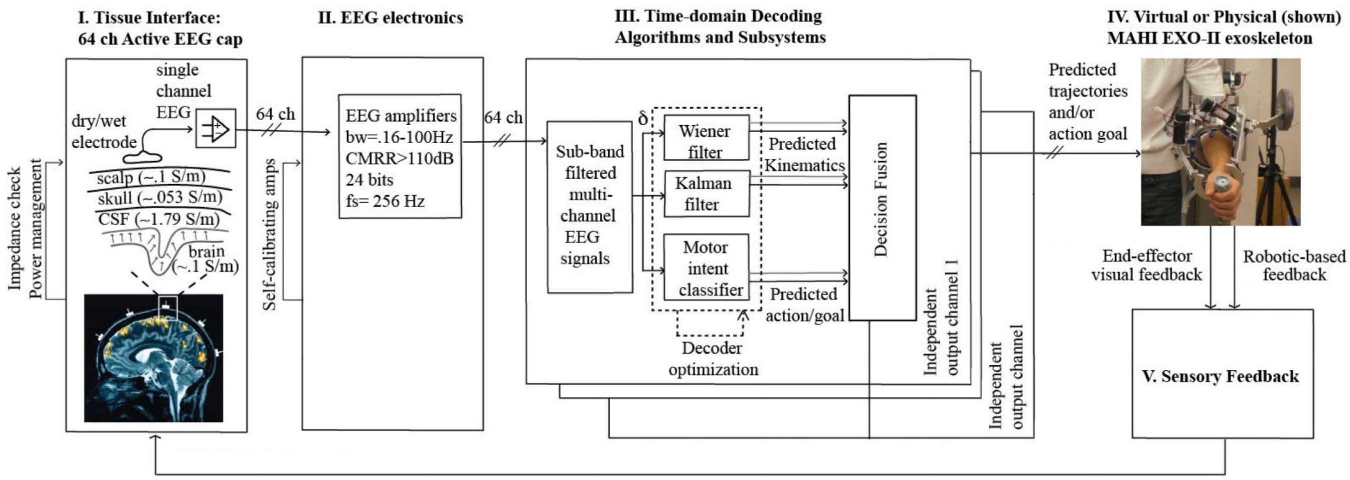

Fig. 2.

Closed-loop BMI system architecture for the control of the MAXI EXO-II using EEG signals.