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Real-time computer modeling of weakness following stroke optimizes robotic assistance for movement therapy

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Abstract—**This paper describes the development of a novel control system for a robotic arm orthosis for assisting patients in motor training following stroke. The robot allows naturalistic motion of the arm and is as mechanically compliant as a human therapist's arms. This compliance preserves the connection between effort and error that appears essential for motor learning, but presents a challenge: accurately creating desired movements requires that the robot form a model of the patient's weakness, since the robot cannot simply stiffly drive the arm along the desired path. We show here that a standard model-based adaptive controller allows the robot to form such a model of the patient and complete movements accurately. However, we found that the human motor system, when coupled to such an adaptive controller, reduces its own participation, allowing the adaptive controller to take over the performance of the task. This presents a problem for motor training, since active engagement by the patient is important for stimulating neuroplasticity. We show that this problem can be solved by making the controller continuously attempt to reduce its assistance when errors are small. The resulting robot successfully assists stroke patients in moving in desired patterns with very small errors, but also encourages intense participation by the patient. Such robot assistance may optimally provoke neural plasticity, since it intensely engages both descending and ascending motor pathways.**

I. Introduction

OVER 700,000 people in the U.S. suffer a stroke each year, and about 80% of these individuals suffer a loss of control of the arm and hand [1]. Intensive sensory motor training stimulates neural plasticity and can increase movement ability following stroke [2-4]. However, it is still not well understood what the optimal sensory motor training techniques are for encouraging motor re-learning. At a basic level, we know that training must be repetitive and intensive, and must engage voluntary descending pathways [5]. Manual assistance that helps limbs move along normative trajectories during training may also improve recovery, simply by stretching soft tissue or perhaps by providing afferent input that enhances neuroplasticity.

Over the past decade, there has been increasing interest in automating sensory motor training following stroke with robotic devices [6-9] that attach to the limbs of patients and assist the patients in performing movements. One motivation for using robotic devices is that long-duration, repetitive training might be delivered more cost effectively. Another motivation is that the robotic device provides a tool for implementing and testing specific therapy algorithms for their efficacy. Initial clinical results with these devices have been promising: acute patients recover better and chronic patients recover more movement ability when they receive extra motor training with a robotic device [9-11]. However, while significant, the movement gains achieved with robotic therapy are still small. An important question is thus whether and how robotic therapy systems can be optimized to better provoke neural plasticity and functional recovery.

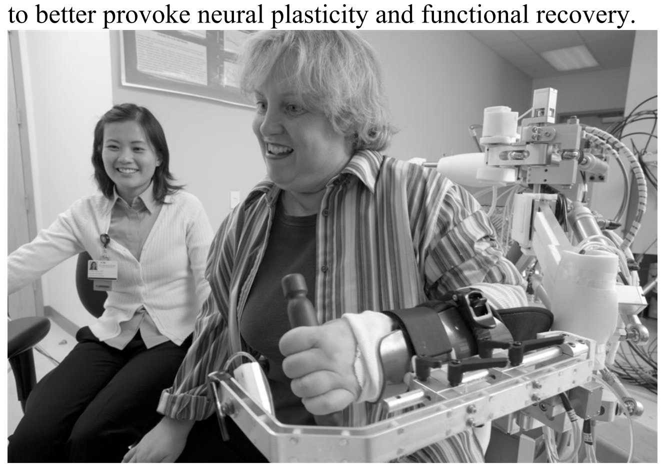

Fig. 1. A person with a stroke engaging in movement training with a robotic exoskeleton called Pneu-WREX.

The goal of this project is to address one possible shortcoming of previous robotic therapy devices. This shortcoming is that the devices do not always "assist-only-as-needed" in helping patients to move. For example, devices have often been made mechanically stiff in order to accurately move a patient's arm [7, 10, 12]. Making a robot stiff removes the ability of the patient to influence the robot, and we hypothesize that it may thus inhibit learning. In the area of locomotor training, for example, it was recently shown in a spinal-injured mouse model that a robotic

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training algorithm that allows movement variability enhances locomotor recovery [13]. Allowing variability makes sense from recent motor learning research: when the nervous system experiences errors caused by errant motor commands, it quickly adapts those commands [14-16]; in other words, kinematic error drives adaptation.

Some previous devices, notably the MIT-MANUS [17] and ARM-In [18], were designed to be compliant to allow some errors, but no general algorithm has yet been proposed to allow such a compliant robot to successfully assist in arbitrary desired movements. For example, if motion in the vertical plane is allowed by the robot, it presents a problem for compliant control. The weight of the average human arm is about 25 N. If the robotic therapy device is compliant, with a stiffness at the low end of what the stiffness of a human therapist's arms might be – 70 N/m [19, 20], a position controller will exhibit an error of 0.36 meters, which is unacceptable if the robot is trying to assist the patient in making specific movements. MIT-MANUS and ARM-In address this problem by weighing each patient's arm for a given configuration and adding an offset term, but this approach is not general enough to provide different levels of assistance to assist with arbitrary spatial movement. Similar problems are experienced with compliant control when trying to move a patient's arm to the end of its range of motion, where resistance to movement can greatly increase due to spasticity and disuse-related changes in soft tissue.

Therapists learn to move patients' arms accurately in the vertical plane and to the end of their range of motion despite the therapist's arms' own compliance, presumably by forming an internal model of the patient's movement ability. In other words, the therapist senses the patient's capability through hands-on interaction and then applies just enough force to allow a patient to succeed in performing a desired movement. The human motor system's ability to form internal models of external dynamics has been well documented in the past decade [21-23], and it seems likely that therapists exploit this ability to control the "external environment" created by their patient's arms.

Here, we show for the first time how a robotic therapy device can learn a general, internal model of the patient's impairment (i.e. the weakness due to both the neurological injury and muscle atrophy) in real-time. We began with a standard model-based adaptive controller for this purpose, but observed an interesting phenomenon when we coupled it to humans. The human motor system took advantage of the possibility to reduce its own participation, and allowed the adaptive controller to take over the performance of the task. This presents a problem for optimizing motor training, since active engagement by the patient is known to be essential for learning [24-26]. We show here, however, that the adaptive controller can be modified by making it attempt to reduce its force. In this case, the human remains intensively engaged in the movement, but the compliant robot still helps make average movement errors small.

In this paper, we first describe the design of the adaptive controller that forms the internal model, and the modification that includes forgetting to prevent patients from reducing their effort when interacting with the robot. We then present data from several experiments with the controller with unimpaired people and people with a chronic stroke. Finally, we present data from one chronic stroke subject who trained regularly with the adaptive controller for eight weeks, significantly improving her movement ability.

II. Methods

The robotic orthosis used for this work is called "Pneu-WREX" [27, 28](Fig. 1). It is a 4 degrees-of-freedom robot based on a passive arm support called WREX, developed for children by [29]. WREX uses elastic bands to balance the weight the arm. Pneu-WREX is a larger version of WREX that uses a spring to balance its own weight, and incorporates pneumatic actuators to generate active forces. The development of the force controller for the pneumatic controller is described in [28]. Essentially, Pneu-WREX is a lightweight exoskeleton that allows a wide range of motion of the arm in 3D space and can apply relatively large forces (upwards of 40 N) to the arm with a bandwidth of about 6 Hz. Pneu-WREX also includes multiple redundant hardware and software safety features.

The adaptive controller that we designed to assist patients in moving is a passivity based algorithm using the sliding surface developed in [30]. The full Lyapunov function candidate used for the Pneu-WREX orthosis contains terms necessary for both the orthosis dynamics and the force dynamics of the pneumatic actuators. See [31] for details. The following sections briefly explain the dynamics of the human and orthosis combination, and the adaptive controller.

A. Orthosis/Human Arm Dynamics

The dynamics of the orthosis and human arm combination can be written as

$$\mathbf{M}(\mathbf{x})\ddot{\mathbf{x}}+\mathbf{C}(\mathbf{x},\dot{\mathbf{x}})\dot{\mathbf{x}}+\mathbf{N}(\mathbf{x},\dot{\mathbf{x}})=\mathbf{F}_r+\mathbf{F}_h \qquad (1)$$

where $\mathbf{x}$ is a $n\times 1$ vector of the workspace coordinates of the hand, $\mathbf{F}_r$ is an $n\times 1$ vector of forces applied by the robot actuators which is mapped by the Jacobian to the hand position, $\mathbf{F}_h$ is an $n\times 1$ vector of forces applied by the human subject at the location of the hand (representing subject contribution), $\mathbf{M}$ is the $n\times n$ generalized inertia matrix, $\mathbf{C}$ is the $n\times n$ Coriolis matrix, and $\mathbf{N}$ is an $n\times 1$ vector of external forces acting on the orthosis, including gravitational, viscous, and potential forces.

B. Adaptive Controller

The controller design uses the sliding surface, $\mathbf{s}$, and reference trajectory, $\mathbf{w}$, developed in [30], and defined

$$\begin{aligned}\mathbf{s}&=\dot{\tilde{\mathbf{x}}}+\mathbf{\Lambda}\tilde{\mathbf{x}}=(\dot{\mathbf{x}}-\dot{\mathbf{x}}_d)+\mathbf{\Lambda}(\mathbf{x}-\mathbf{x}_d)\\ \mathbf{w}&=\dot{\mathbf{x}}_\mathbf{d}-\mathbf{\Lambda}\tilde{\mathbf{x}}=\dot{\mathbf{x}}_\mathbf{d}-\mathbf{\Lambda}(\mathbf{x}-\mathbf{x}_d)\end{aligned} \qquad (2)$$

where $\mathbf{x}$ and $\mathbf{x}_d$ are $n \times 1$ vectors of the actual and desired location of the hand, respectively, and $\mathbf{\Lambda}$ is an $n \times n$ symmetric, constant, positive definite, gain matrix.

The standard control law for this method is

$$\mathbf{F}_r = \mathbf{Y}(\mathbf{x}, \dot{\mathbf{x}}, \mathbf{w}, \dot{\mathbf{w}})\hat{\mathbf{b}} - \mathbf{K}_P \tilde{\mathbf{x}} - \mathbf{K}_D \dot{\tilde{\mathbf{x}}} \quad (3)$$

where $\mathbf{K}_P$ and $\mathbf{K}_D$ are symmetric, constant, positive definite gain matrices and $\mathbf{Y}\hat{\mathbf{b}}$ is a model of the system dynamics and is defined as

$$\mathbf{Y}\hat{\mathbf{b}} = \hat{\mathbf{M}}\dot{\mathbf{w}} + \hat{\mathbf{C}}\mathbf{w} + \hat{\mathbf{N}} \quad (4)$$

where $\hat{\mathbf{M}}$, $\hat{\mathbf{C}}$, and $\hat{\mathbf{N}}$ are estimates of the dynamics of the orthosis and arm combination, $\mathbf{Y}$ is a $m \times n$ matrix of known functions of $\mathbf{x}$, $\dot{\mathbf{x}}$, $\mathbf{w}$, and $\dot{\mathbf{w}}$, and $\hat{\mathbf{b}}$ is an $m \times 1$ vector of parameter estimates.

In order to model arm weakness, we include the contribution of the subject in the control law so that

$$\mathbf{F}_r = \mathbf{Y}\hat{\mathbf{b}} - \hat{\mathbf{F}}_h - \mathbf{K}_P \tilde{\mathbf{x}} - \mathbf{K}_D \dot{\tilde{\mathbf{x}}} \quad (5)$$

where $\hat{\mathbf{F}}_h$ is an estimate of the subject contribution, which we assume can be modeled as

$$\hat{\mathbf{F}}_h = \mathbf{Y}\hat{\mathbf{h}} \quad (6)$$

where $\hat{\mathbf{h}}$ is an $m \times 1$ vector of parameter estimates describing the contribution of the subject. Using (6) in (5) and defining $\hat{\mathbf{a}} = \hat{\mathbf{b}} - \hat{\mathbf{h}}$ gives the final control law as

$$\mathbf{F}_r = \mathbf{Y}\hat{\mathbf{a}} - \mathbf{K}_P \tilde{\mathbf{x}} - \mathbf{K}_D \dot{\tilde{\mathbf{x}}} \quad (7)$$

where $\mathbf{Y}\hat{\mathbf{a}}$ represents a model of movement impairment, i.e. the difference between the forces required to move along a desired trajectory and the contribution of the subject towards the same goal. In the case of complete arm impairment, $\mathbf{Y}\hat{\mathbf{h}} = 0$, and the controller will adapt to provide all of the necessary forces to complete movements. In the case of an unimpaired arm, $\mathbf{Y}\hat{\mathbf{h}} = \mathbf{Y}\hat{\mathbf{b}}$, and controller adaptation will be minimal as the subject contributes the necessary forces to complete movements.

The estimates are adapted according the update law

$$\dot{\hat{\mathbf{a}}} = -\mathbf{\Gamma}^{-1}\mathbf{Y}^T \mathbf{s} \quad (8)$$

where $\mathbf{\Gamma}$ is a symmetric, constant, positive definite gain matrix. The controller defined by (7), and (8) is globally asymptotically stable (following an analysis similar to [32]).

For the controller presented in this paper we developed a general representation of arm weakness using radial basis functions [33] as the regression matrix $\mathbf{Y}$. Essentially, the use of these basis functions allows the model parameters to vary as an arbitrary function of the state (i.e. position and velocity) of the arm, where the robot learns this arbitrary function by experience.

C. Assist-As-Needed Modification

We added a modification to the model update law (8) in order to minimize the force applied to the subject, motivated by the work of [34]. We desire that the controller will decay the force applied by the orthosis when the subject is able to complete movements without assistance. In particular, the partial derivative of the modeled arm weakness force with respect to time should behave according to

$$\frac{\partial}{\partial t}(\mathbf{Y}\hat{\mathbf{a}}) = \mathbf{Y}\dot{\hat{\mathbf{a}}} = -f_r \mathbf{Y}\hat{\mathbf{a}} \quad (9)$$

where $\mathbf{Y}\hat{\mathbf{a}}$ is the force applied to the subject's arm by the adaptive controller according to (3), and $f_r = 1/\tau$ is the forgetting rate of the robot (τ = time constant). In general, $\mathbf{Y}$ is an $n \times m$ matrix with $m > n$ and rank n. Thus there are an infinite number of solutions for $\dot{\hat{\mathbf{a}}}$ that satisfy (9). For our controller we seek the shortest solution for $\dot{\hat{\mathbf{a}}}$. This is done by solving the constrained minimization problem

$$\min : \left\{ \mathrm{f} = \tfrac{1}{2}\dot{\hat{\mathbf{a}}}^T \dot{\hat{\mathbf{a}}} : \mathrm{g} = -\mathbf{Y}\dot{\hat{\mathbf{a}}} - f_r \mathbf{Y}\hat{\mathbf{a}} = 0 \right\} \quad (10)$$

The minimum solution to (10) is

$$\dot{\hat{\mathbf{a}}} = -f_r \mathbf{Y}^T \left(\mathbf{Y}\mathbf{Y}^T\right)^{-1} \mathbf{Y}\hat{\mathbf{a}} \quad (11)$$

This term is added to the right side of (8) to create the modified parameter update law:

$$\dot{\hat{\mathbf{a}}} = -f_r \mathbf{Y}^T \left(\mathbf{Y}\mathbf{Y}^T\right)^{-1} \mathbf{Y}\hat{\mathbf{a}} - \mathbf{\Gamma}^{-1}\mathbf{Y}^T \mathbf{s} \quad (12)$$

Lyapunov stability analysis of the modified parameter update law (using a method similar to that given in [32]) shows stability the sense of uniform ultimate boundedness. This bound is a function of the forgetting rate, f_r. In practice, this forgetting rate weighs the balance between tracking error and robot effort.

D. Experimental Methods

We tested both versions of the adaptive controller (i.e. with and without the forgetting term) with three unimpaired adults and nine volunteers with a chronic stroke. For these experiments, the proportional gain, $\mathbf{K}_P$, was set to 70 N/m. All experiments were approved by the IRB of U.C. Irvine and subjects provided informed consent.

The goal of these initial experiments was to determine how well the adaptive controller "assisted-as-needed" in helping a person achieve a desired movement. The subjects were instructed to try to follow a target cursor on a computer display by controlling a second cursor which represented the endpoint of the orthosis. The target cursor moved back and forth between two targets along a minimum jerk trajectory with peak velocity of 0.12 m/sec. In arm coordinates, the targets were spaced 30 cm apart in the horizontal plane at chest level approximately 45 cm in front of the body. For the unimpaired subjects, a constant, downward load of 8.9 N was applied to the arm to make the movements more effortful, like movements by stroke patients are.

We evaluated two experimental conditions. For the first condition (*Subject Relaxed to Active* condition), the subjects began with their arms relaxed for five back-and-forth motions of the robot. During this period, the robot learned a model of the forces needed to lift the subject's arm and move it between the targets. Then, beginning at the sixth back-and-forth motion and continuing for 15 more, the subject began to actively attempt to move the arm between the targets. The question of interest for this condition is whether the robot then was "smart enough" to sense the subject's movement ability and allow the subject to begin to perform the task on his or her own.

In the second experimental condition (*Subject Always Active* condition), the subjects simply moved back-and-forth between the targets 20 times. The task of the adaptive controller in this case was to learn how much force the subjects needed to successfully achieve the desired movement. An adaptive controller that performed poorly in this case might gradually "take over" performance of the task from the subject, for example, providing too much support.

For both experimental conditions, we measured performance of the controller without forgetting, and with the forgetting rate f_r set to 0.1, with the order of the conditions randomized.

We also conducted a pilot study of the therapeutic efficacy of the controller. In this study, one female chronic stroke subject (aged 46, 11 years following stroke) practiced movements with the adaptive, assist-as-needed controller three sessions per week for eight weeks, with each session lasting one hour. The controller, with a forgetting term, was integrated into simple virtual reality games that simulated functional activities like reaching for items on a shelf, picking up an egg and cracking it over a pan, and cleaning a window (see [31] for description of games). The subject was evaluated before and after the training period with standard clinical measures of upper arm movement ability, and during the training period with several robot-based measures of motor ability.

III. Results

We developed an adaptive controller that learns in real-time a model of the movement impairment of a subject as they attempt to move their arm with the assistance of a robotic orthosis. Fig. 2 shows the vertical forces learned by the robot controller for a moderately impaired stroke subject during the *Subject Relaxed to Active* condition experiment at different time samples as a function of the horizontal and vertical position of the subject's hand. The robot learned to apply large forces when the subject relaxed for the first 5 movements (Surface A), and continued to apply large forces after the subject actively participated in the next 15 movements (Surface B) when $f_r = 0$, When the subject repeated the experiment with $f_r = 0.1$, the robot learned to apply smaller forces (Surface C), although these forces were still non-zero as the subject was impaired.

We analyzed further how human subjects interacted with the adaptive controller with and without including a forgetting term in the controller, by examining the vertical force that the robot learned to apply as a function of time (Fig. 3). For the *Subject Relaxed to Active* condition, when the subjects relaxed their arms, the robot quickly (in about 10 sec) learned the amount of vertical force needed to lift the arms to the targets' height. When the subjects then begin trying to move their arms, the pattern of change in vertical force applied by the controller depended on whether forgetting was incorporated. Without forgetting, the controller did not let the subject "take over" performance of the task, and the vertical force stayed large, relieving the weight of the subject's arm. With forgetting, the controller gradually reduced its force, requiring the subjects to begin lifting their own arms. In both cases the vertical tracking error was small. Thus, including the novel forgetting term into the standard adaptive controller better engaged the subject's efforts, while still keeping tracking error small.

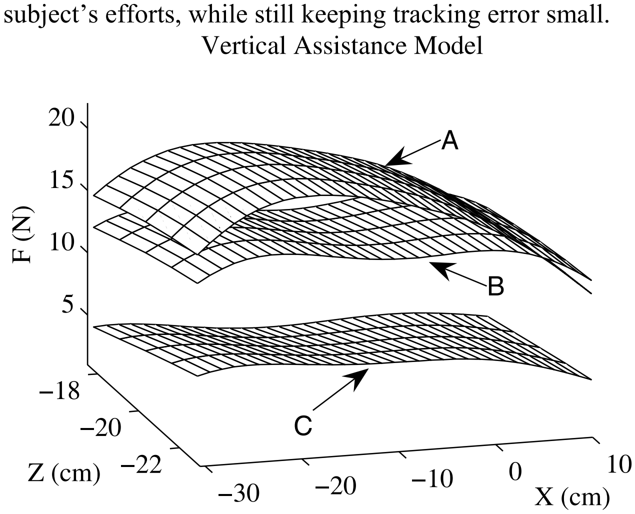

Fig. 2. Impairment model built during target tracking in *Subject Relaxed to Active* condition for a moderately impaired stroke subject Fugl-Meyer score = 30). Surfaces represent vertical force output of the model as a function of vertical (Z) and left to right (X) position, at a distance of 45 cm out from body center. Surface A shows the model after the robot completed 5 movements with the subject relaxed (without forgetting). Surface B shows the model after the subject participated in the next 15 movements without forgetting. Surface C shows the model after the subject repeated the experiment, relaxing for 5 movements and then completing the next 15 movements with forgetting equal to 0.1.

In the *Subject Always Active* condition, the subjects allowed the controller to take over some degree of the tracking task when the controller did not incorporate forgetting. This is evident in Fig. 3, which shows that the robot force gradually increased as the subjects practiced moving. For each subject, the controller took over most of the vertical force, converging to levels similar to those at the end of the *Subject Relaxed to Active* condition test. For both conditions, the vertical assistance from the controller converged to an amount that varied appropriately with the impairment level of the subject.

Fig. 4 shows a summary of the vertical assistance force learned by the robot, and the tracking error achieved by the subject, with and without forgetting. Subjects contributed significantly more force to the tracking task with forgetting present in the adaptive controller (t-test, $p < 0.05$). Tracking error was under 1.5 cm even for the most impaired subjects.

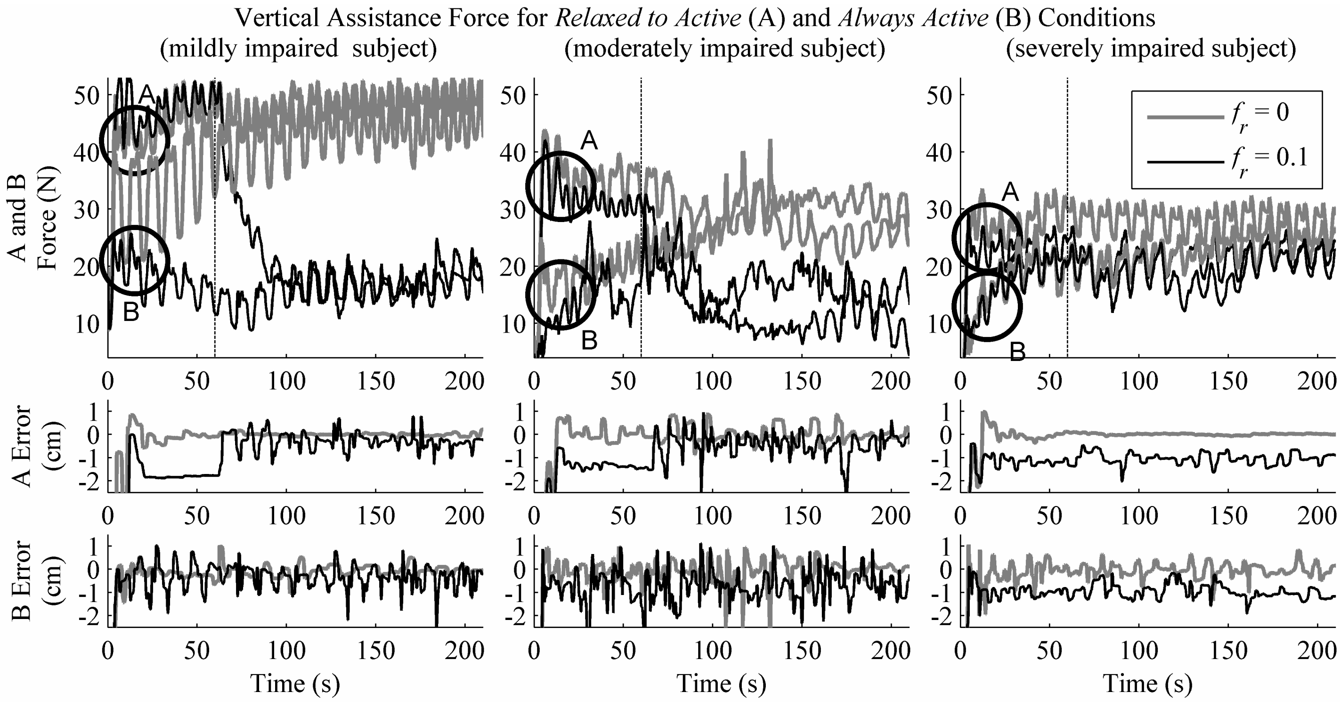

Fig. 3. Vertical assistance force learned by the robot and position tracking error during *Subject Relaxed to Active* condition (labeled "A" in the top force plots) and *Subject Always Active* condition (labeled "B"). Left column is data from a mildly impaired subject (Fugl-Meyer score = 53), middle from a moderately impaired subject (Fugl-Meyer score = 30), and right from a severely impaired subject (Fugl-Meyer score = 16). The dotted vertical line marks the end of the 5th back and forth movement. Notice that tracking errors are consistently small, indicating that the robot successfully assisted the subjects in moving. However, the amount of assistance force is smaller when the robot has forgetting. Without forgetting, the human lets the robot assistance force gradually increase (see black lines labeled "B").

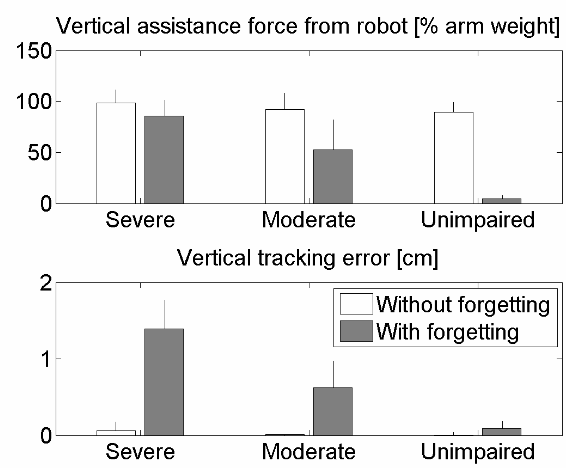

Fig. 4. Mean vertical assistance force provided by Pneu-WREX as a function of patient impairment (severely impaired, Fugl-Meyer < 24, n = 4; moderately impaired, 24 < FM < 66 n = 4; unimpaired, FM = 66, n = 3). The task was to track a cursor that moved between two targets placed in the frontal plane at chest height. With a forgetting rate in the adaptive controller, the robot contributed significant less support force (grey bars versus white bars in top plot, paired t-test across subjects, $p < 0.05$), indicating that the subjects exerted more force as they performed the task. Tracking error increased with forgetting present, but was still under 1.5 cm even for severely impaired patients who could not do the task without robot assistance. Data is from *Relaxed to Active* condition. The error bars show one standard deviation across subjects.

We also used the adaptive, assist-as-needed controller in a pilot study of motor training with the robot for one chronic stroke subject. Quantitative and clinical measures of the subject's movement ability show that the subject's movement ability improved. Fig. 5 shows the peak speed of movement of the subject in the vertical direction during a test in which she was asked to move as fast as possible without help from the robot. The subject's Fugl-Meyer arm score changed from a rating of 27 to 30, an 11 % change.

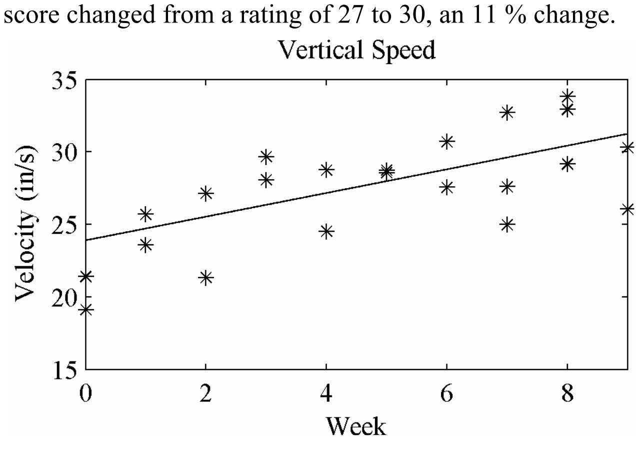

Fig. 5. Peak vertical speed of movement for chronic stroke subject during movement training increased ($p < 0.001$ linear regression).

I. Discussion and Conclusion

These results are a step forward in addressing what we believe is a fundamental problem in robot-assisted movement training: how can a device encourage effort from the patient, assisting only as needed, while remaining compliant so as to allow the patient to create some error? We found that an adaptive controller modified to include forgetting can be used to form a real-time model of the patient's weakness and encourage effort. The forgetting term appears necessary because the human motor system is structured to reduce effort when errors are small. This finding is consistent with recent work in motor adaptation that found that unimpaired subjects minimize both kinematic error and muscle effort when adapting to novel dynamic environments [11, 14, 35]. Using a computational model of motor adaptation and an optimization approach, [14] showed how the inclusion of a forgetting term in an error-based controller can allow unimpaired subjects to learn an internal model of a force field during walking, without experience large errors. The controller developed here is similar, although more sophisticated as it achieves the task of moving a limb along any arbitrarily-defined trajectory with such "assistance-as-needed".

The pilot data from using the controller to train one person with a chronic stroke was promising: the subject improved both clinical and quantitative scores of movement ability. We plan now to test whether this "assist-as-needed" adaptive controller is therapeutically more effective than a controller without forgetting, in a randomized, controlled clinical test with 30 patients. Because it more intensely engages the patient's descending motor tracts, while also helping create normative movements and thus afferent input that is correlated with motor intent, we hypothesize that it will be more effective.

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