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Rehabilitation Robotics: Performance-Based Progressive Robot-Assisted Therapy

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Abstract. In this paper we describe the novel concept of performance-based progressive robot therapy that uses speed, time, or EMG thresholds to initiate robot assistance. We pioneered the clinical application of robot-assisted therapy focusing on stroke—the largest cause of disability in the US. We have completed several clinical studies involving well over 200 stroke patients. Research to date has shown that repetitive task-specific, goal-directed, robot-assisted therapy is effective in reducing motor impairments in the affected arm after stroke. One research goal is to determine the optimal therapy tailored to each stroke patient that will maximize his/her recovery. A proposed method to achieve this goal is a novel performance-based impedance control algorithm, which is triggered via speed, time, or EMG. While it is too early to determine the effectiveness of the algorithm, therapists have already noted one very strong benefit, a significant reduction in arm tone.

Keywords: rehabilitation robotics, stroke, robot-aided neurorehabilitation, adaptive algorithm

Introduction

One overarching goal drives our research and development activities: to revolutionize rehabilitation medicine by applying robotics and information technology that can assist, enhance, and quantify rehabilitation—particularly neuro-rehabilitation. Unlike predecessors who used robotics as an assistive technology for the disabled, our research uses robots and computers to support and enhance the clinicians' productivity as they facilitate a disabled individual's functional recovery. The embodiment of this goal is a new class of interactive, user-friendly, clinical devices designed not only for evaluating patients, but also for delivering therapy via engaging "video games." The science is the understanding of the neuro-muscular, motor learning, and neuro-recovery processes. The engineering is the design and control of human-machine interfaces in general, and robot-aids for different limbs and body segments in particular. A goal for both science and engineering is the analysis of patient movement and force generation. Our overarching goal might seem unduly ambitious; a "technology push" rather than a "market pull." Yet as with other archaic industries, the rehabilitation field is ripe for a change. Consider that:

(1) Health care providers are disclosing systematic and significant losses.
(2) The demand for rehabilitation services will increase in the coming decades, since graying of the population will almost certainly increase the numbers of cases.
(3) The expected increase in the number of patients will increase the nation's health care financial burden. In fact, Health Care Financing Administration (HCFA) projected health care costs to surpass 16.6% of the total Gross National Product (GNP) in the year 2007 ($2.1 trillion), notwithstanding significant pressure towards cost containment.

Robotics and information technology can provide an overdue transformation of rehabilitation clinics from labor-intensive operations to technology-assisted operations. Robot-aids not only are more efficient in delivering certain routine physical and occupational therapy activities, but also provide a rich stream of data that can facilitate patient diagnosis, customization of the therapy, and maintenance of patient records (at the clinic and at home).

Significance

In the US health care costs have escalated rapidly over the past three decades, and are projected to surpass 16.6% of the total GNP in the year 2007 ($2.1 trillion), despite significant current efforts to contain and reduce costs. Graying of the population will almost certainly aggravate this problem; according to World Health Organization (WHO) in the coming years the population over 65 years old should increase by 88%. This group is particularly prone to suffer a cerebral vascular accident (stroke) since the relative incidence of stroke doubles for every decade after 55 years old further burdening the system. In fact, stroke is the leading cause of permanent disability in the US Over 700,000 Americans per year suffer a stroke; more than half survive; in the US about four million stroke victims are alive today (Gresham et al., 1995). The economic burden of stroke was estimated to be $30 billion, equal to 3% of national health expenditures (American Heart Association). A similar picture can be drawn for Europe and Japan. For example, each year there are over 920,000 new stroke cases in Europe with a 22% 30 day mortality. Of the survivor group, about 80% will need rehabilitation (Brainin et al., 2000). Taking Belgium as an average of continental disparities, there are 20,000 new stroke cases per year of a total population of 10 million (1:500 inhabitants). Of the 20,000 new stroke cases, the mortality rate is 48.6% within the first eight weeks following the onset of the stroke and of the 51.4% survivor group, 82% will need therapy. Japan presents an even bleaker perspective, with the lowest average birth rate among industrialized nations of 1.3. If nothing changes, by 2025 there will be two working-age adults (20 to 65 years old) for every retirement-age person (65 and older). Graying of the population is not the only factor pointing to a potential increase in the need for rehabilitation services. Pharmacological agents for neuro-protection under development (e.g., nerve growth factors, better receptor blockers, anti-oxidants, anti-inflammatory agents, and blood-clot dissolving agents) may eventually reduce the severity of stroke and increase the survival rate, yet these advances will also increase the percentage of stroke victims who require rehabilitation.

At present, physical and occupational therapy comprise the standard and presumably beneficial form of treatment for these impairments, but they are labor-intensive and expensive. Until recently, health care providers have reduced rehabilitation costs primarily by shortening inpatient hospital stays. Once the practical limit of abbreviated inpatient stays is reached, further efficiencies will be attainable chiefly by addressing clinical practices themselves. While skilled therapists can achieve good results with even rudimentary equipment, the maximum effectiveness of their existing "toolbox" is rapidly being reached. To increase productivity new tools are needed. Our research suggests that robotics and information technology can transform rehabilitation clinical practice from its present basis in manual operations to a more technology-rich operation. This situation creates a pressing need for new therapeutic strategies to increase productivity while optimizing the quality of care, and an opportunity to take advantage of recent advances in technology—especially in robotics, sensing, information processing, and telecommunications.

Figure 1. Stroke patient during robot-aided therapy at the burke rehabilitation hospital (White Plains, NY).

Clinical Perspective

The centerpiece of our ongoing research and development program is MIT-MANUS, a robot specifically designed and built for clinical, neurological applications (Hogan et al., 1995; Krebs et al., 1998).[1] Because the mechanical system was designed to have a low intrinsic end-point impedance, with extremely low inertia and friction (i.e., it is highly "back-drivable"), MIT-MANUS is able to move smoothly and can rapidly comply with a patient's motor actions (Krebs et al., 1999, 2001). The robot sensors permit accurate and essentially continuous measurement of the key variables relevant to motor behavior, namely position, velocity, and interaction forces. MIT-MANUS has two degrees-of-freedom (DOF) that can move a patient's shoulder, elbow, and hand in a horizontal, gravity-eliminated plane. During therapy, the person's hemiparetic arm is placed in a customized arm support that is attached to the end-effector (i.e. handle) of the robot arm. As patients move the robot arm toward a designated target, a video screen in front of them provides visual feedback of the target location and movement of the robot handle (see Fig. 1). If the person is unable to move, the robot guides the hand to the target in a similar manner as a therapist provides hand over hand assistance during conventional therapy.

Research to date has shown that repetitive task-specific, goal-directed, robot-assisted therapy can be effective in reducing motor impairments in the affected arm after stroke (Aisen et al., 1997; Volpe et al., 1999, 2000; Krebs et al., 2000). Table 1 summarizes the outcome of seventy-six stroke patients exhibiting a unilateral lesion who were enrolled in the initial clinical trials, which lasted approximately 5 weeks per patient. Patients were randomly assigned to experimental and control groups. The experimental group received an hour per day of robot-aided therapy exercising the shoulder and elbow. The control group received an hour per week of "sham" robot-aided therapy with the same video games. The results of the initial studies showed statistically significant differences between the experimental and control group for shoulder and elbow (the focus of the exercise routines), but no differences for wrist and fingers (which were not exercised), as measured by standard clinical instruments, e.g., the MRC test of Motor Power and Motor Status Score (Medical Research Council/Guarantors of Brain, 1986; Ferraro et al., 2002). In fact, more recent results with additional patients (Volpe et al., 2001) confirmed that this initial approach of delivering mass practice therapy significantly improved recovery by a factor of two in terms of impairment reduction of inpatients (in absolute terms, it

Table 1. Change during acute rehabilitation (76 patients): Experimental (RT) vs. control (ST) group—$\Delta 1$: Score change from hospital admission to discharge; MP is the motor power; MS1 is the motor status score for Shoulder and Elbow (Medical Research Council/Guarantors of Brain, 1986; Ferraro et al., 2002); $p < 0.05$ for statistical significance (*).

Group (76 inpatients)	MP (range/20) $\Delta 1^*$	MS1 (range/40) $\Delta 1^*$
RT (40)	3.99	8.15
ST (36)	2.0	3.42

Table 2. Change during outpatient rehabilitation (20 patients): Experimental (RT) group—Δ2: Score change from admission into the protocol to completion; MP is the motor power; MS1 is the Motor Status Score for Shoulder & Elbow (Medical Research Council/Guarantors of Brain, 1986; Ferraro et al., 2002); $p < 0.05$ for statistical significance (*).

Group (20 outpatients)	MP (range/20) Δ2*	MS1 (range/40) Δ2*
RT admission	13.7	24.7
RT discharge	14.9	26.1

means an additional 10% improvement). Table 2 summarizes that a similar approach showed an additional 5% improvement for outpatients (6 weeks program with 3 sessions per week) (Fasoli et al., 2003). In this case, the outpatients at admission were their own control and showed statistically significant differences between admission and discharge for shoulder and elbow (the focus of the routine).

Optimal Therapy

There is no reason to believe that a "one-size-fits-all" optimal treatment exists. Instead therapy should be tailored to each patient's needs and abilities. Robot-assisted therapy can be delivered in a variety of ways to reduce motor impairment and enhance functional motor outcomes. Goal-directed therapeutic "games" can be designed to address motor impairments including poor coordination, impaired motor speed or accuracy, decreased grasp or dexterity, and diminished strength, as well as addressing cognitive or perceptual impairments. Depending on the survivor's impairment and lesion, robotic aids can provide passive, active-assistive, active, and active-resistive exercises. They can also deliver therapeutic approaches with no equivalent experience in nature (Patton and Mussa-Ivaldi, 2001). The understanding of what constitutes the most appropriate therapy has the potential to become an intensively active topic of research.

One innovative modality of robotic therapy developed recently in our lab is the inclusion of specific, movement-related feedback and control parameter specification via a performance-based progressive algorithm. The stroke rehabilitation therapy administered during our initial clinical trials was a fixed, repetitive exercise cued by a video display. It consisted of a series of assisted point-to-point moves, which appeared to be well suited for patients with very limited movement ability. During therapy, an impedance controller[2] with constant stiffness and damping was used to guide the patient's arm with a minimum-jerk movement of constant duration from the starting position (*) to the end position (**). The effect of the stiffness of the controller can be visualized as a potential energy field about a moving desired position (Fig. 2) that limits deviation along the target axis, y, and its normal axis, x. Specifically, the command forces along these axes are given by

$$F_{c,x} = -kx - b\dot{x} \tag{1}$$

$$F_{c,y} = -k(y - y_{m.j.}) - b\dot{y} \tag{2}$$

$$y_{m.j.} = l_m\left[10\left(\frac{t}{t_m}\right)^3 - 15\left(\frac{t}{t_m}\right)^4 + 6\left(\frac{t}{t_m}\right)^5\right] \tag{3}$$

where $y_{m.j.}$ is the controller's minimum jerk movement, k is the controller stiffness, b is the controller damping, l_m is the length of movement, and t_m is the duration of movement.

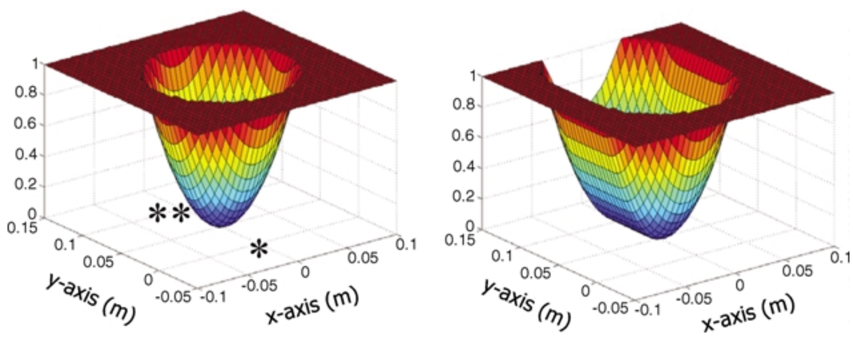


Figure 2. Impedance controllers. The left plot shows the potential energy of the controller employed during the initial trials. The right plot shows the potential energy for the novel adaptive controller.

The potential energy field of the new impedance controller is also shown in Fig. 2. While the stiffness of the previous controller tends to impede the patient from moving ahead of the desired trajectory, the proposed controller allows capable patients to reach the target unassisted because $F_{c,y} = 0$ in the range $y_{m.j.} \leq y \leq l_m$. The command forces are defined by

$$F_{c,x} = -kx - b\dot{x} \tag{4}$$

$$F_{c,y} = \left\{ \begin{array}{c|c} -k_{bw}(y - y_{m.j.}) - b\dot{y} & y < y_{m.j.} \\ 0 & y_{m.j.} \leq y \leq l_m \\ -k(y - l_m) - b\dot{y} & y > l_m \end{array} \right\} \tag{5}$$

During the proposed therapy, the time allotted for the patient to make the move, t_m, and the primary stiffness of the impedance controller, k, are varied based on the patient's performance and variability, but the "back wall" stiffness, k_{bw}, is held constant. By using a performance-based, progressive algorithm yet to be defined, the therapy continuously challenges the patient.

This approach appears to be particularly well suited if we consider typical examples of unassisted patient movements shown in Fig. 3. This figure illustrates quite well that different stroke lesions can lead to quite different kinematic behavior during reach. The first patient makes pretty fast movements but aims poorly, while the second one aims well but moves very slowly. The novel modality of the proposed robot-assisted therapy guides the hand of the patient that aims poorly without holding him/her back and assists the other patient in making faster movements.

Four Performance Measures

In an effort to keep patients motivated during therapy sessions, a video display provides the patient with positive reinforcement during the session. The height and color of four bars on the display reflect patient performance. The four performance measures grade patients' ability to initiate movement (PM1), to move from the starting position to the target (PM2), to aim their movement along the target axis (PM3), and to reach the target position (PM4) (Krebs et al., 2001a, 2001b). PM1 records how many times the patient initiated the "game" by moving the arm above a speed threshold or

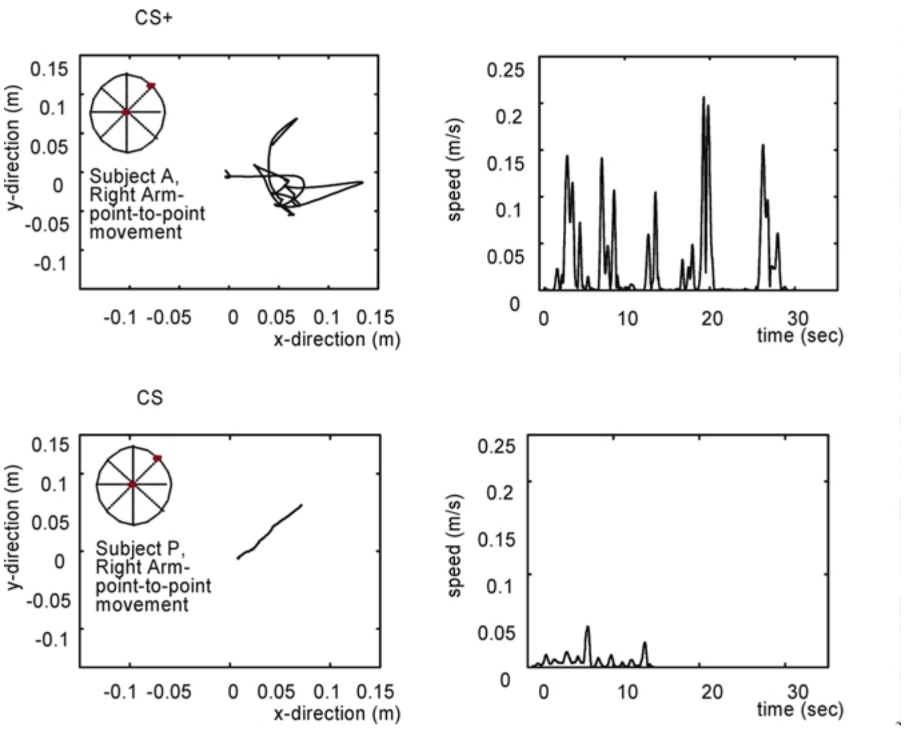


Figure 3. Reaching movements made by patients with corpus striatum lesion—CS (8.9 cm^3) and corpus striatum plus cortex lesion—CS+ (109.9 cm^3). The left column shows a plan view of the patients' hand path attempting a point-to-point movement. The right column shows hand speed.

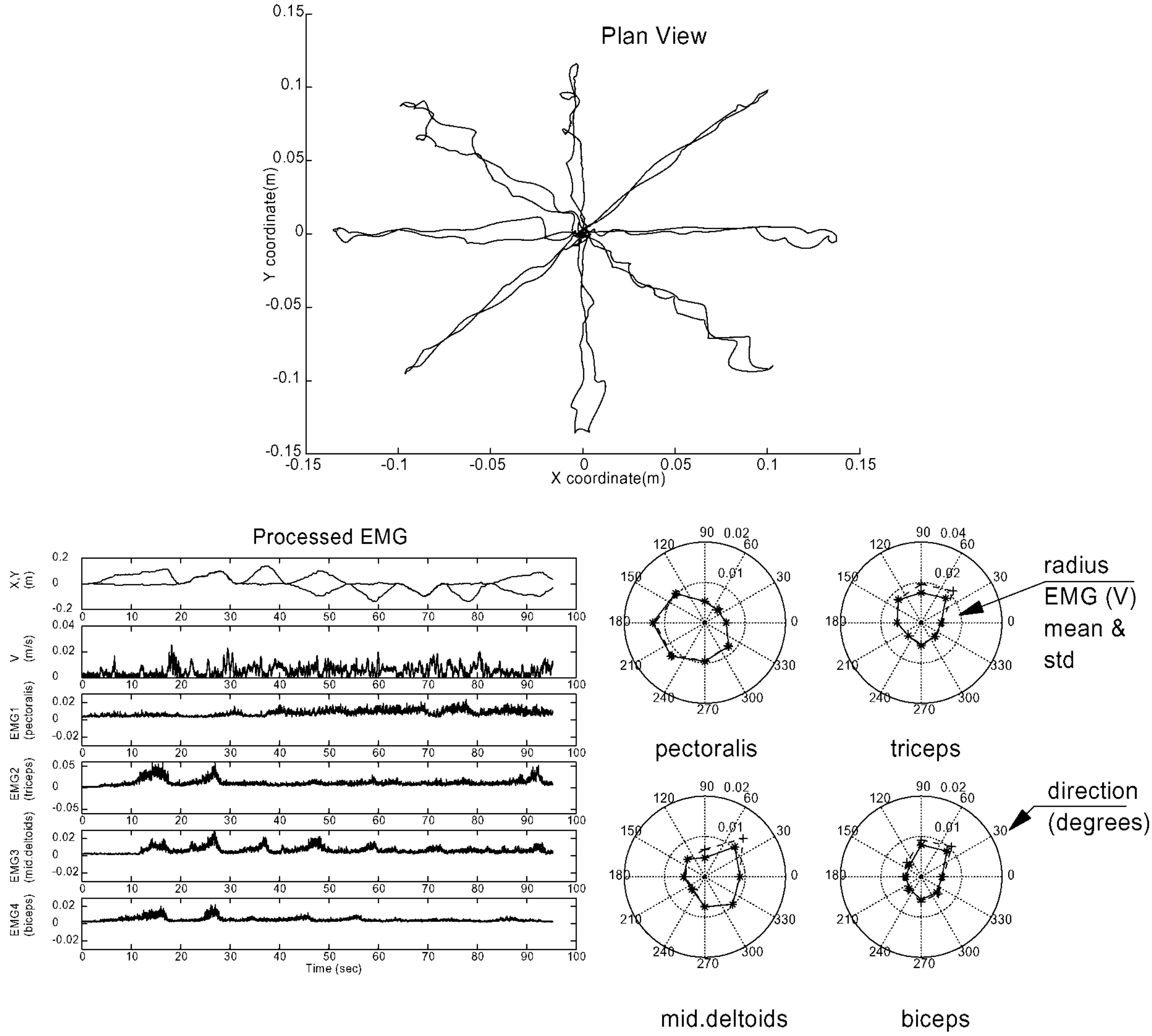


Figure 4. Example of EMG activation for patient SK Top figure shows the plan view of the unassisted reaching movement. The lower left set shows the hand position in x and y coordinates, the speed of movement, and the EMG activation for the pectoralis major, triceps, middle deltoids, and biceps. The lower right set shows the polar distribution for the processed EMG. The solid line represents the mean and the dashed line the standard deviation of repeated trials.

an electromyographic activation (EMG). PM2 is used to adjust the time allotted for the move. PM3 is used to adjust the controller stiffness. PM4 records the maximum distance the patient moved along the target axis.

The PM1 measurement evaluates how many times the patient initiated movement toward the eight outer targets during the game. We are using three different modes to determine movement initiation. If the patient fails to trigger the game for any of the three modes, the game commences after 2 seconds. The first mode requires patients to move the arm above a modest velocity threshold. It can be used with any patient independent of his/her impairment level. While its use might be obvious with mild and moderate strokes, one should notice that the approach could also work with severe strokes. Although restrained by seatbelts, patients engage their trunk to initiate the movement (no particular instruction is given but to try to reach the target). This mode motivates the patient to try to move and not just passively let the robot drive the arm. This mode is the "default," primarily because it does not require any additional piece of hardware.

As mentioned earlier, the impedance controller's desired trajectory has a minimum-jerk profile. Using the yet-to-be-defined, performance-based, progressive algorithm, the duration of the minimum jerk trajectory (t_m) will be varied. The velocity threshold is defined to be 10% of the maximum speed of this minimum-jerk trajectory, namely:

$$V_{\text{threshold}} = 0.10\left[1.875\left(\frac{l_m}{t_m}\right)\right] \tag{6}$$

where l_m is the distance between targets in meters. When the patient's speed is greater than $V_{\text{threshold}}$, the novel impedance controller initializes the game. Since the duration of the minimum jerk trajectory is changed with patient performance, success in initiating movement is also redefined. That is, as t_m increases, $V_{\text{threshold}}$ decreases, and vice versa.

The second mode uses processed EMG signals to trigger the movement using a Bagnoli$^{\text{TM}}$ from Delsys (Boston, USA). We collected EMG activity in 14 muscles of the shoulder and elbow during point-to-point movements for normal subjects and stroke patients, and then selected a subset of these muscles based on accessibility, ease of accurate electrode placement on muscle, and map of EMG activity. During all the required movements, at least one of the following four muscles was active: pectoralis major, middle deltoid, biceps, and triceps. The game is triggered when at least one of the muscles' processed EMG activity increases above a threshold. The third mode is very similar to the second one, but for each required movement direction, the game is triggered only after seeing an increase in EMG activation in a particular muscle.

The muscle is considered active if the processed EMG exceeds the baseline activity by more than 3 standard deviations for at least 30 msec (to exclude heartbeat). The EMG signal is processed with a high-pass filter (Butterworth, 2nd order, 10 Hz), rectified, and then processed with a low pass filter (moving average, 60 msec).

The PM2 and PM3 measurements evaluate a patient's performance during each game, which consists of moves to and from eight equally spaced radial targets. Figure 5 depicts the most promising candidates for PM2, the ability to move (top row), and for PM3, the ability to aim (bottom row), calculated from data gathered from a representative patient at admission and discharge. The first column depicts kinetic measurements, whereas the second column is kinematic.

The kinetic measurement for PM2 is the average power along the target axis (PM2a—borrowing the term from electrical engineering, PM2a is the "Active Power"), and the kinematic measurement is the average deviation from the robot control system's minimum jerk trajectory (PM2b).

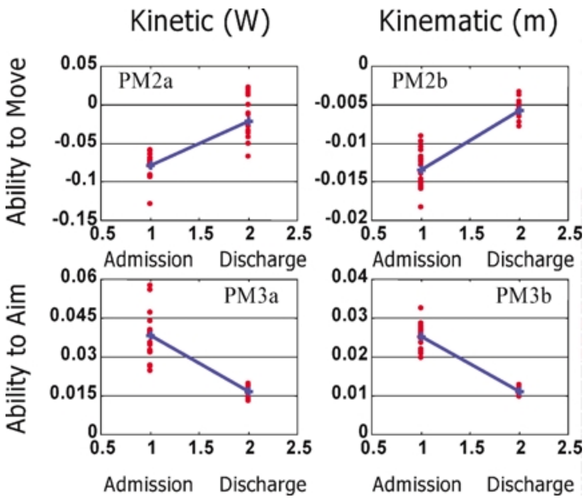


Figure 5. Promising robot measures to define PM2 and PM3—clinical results.

$$\text{PM2a} = \frac{1}{N}\sum_{i=1}^{N}[F_y(i)\dot{y}(i)] \tag{7}$$

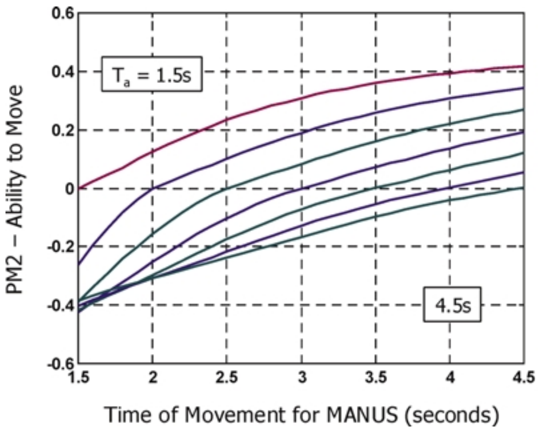
$$\text{PM2b} = \frac{1}{N}\sum_{i=1}^{N}[y(i) - y_{m.j.}(i)] \tag{8}$$

where F_y is the interaction force along the target axis, $\dot{y}$ is the velocity along the target axis, y is the position along the target axis, y_{mj} is the prescribed minimum jerk trajectory of the "back wall" of the new impedance controller, and N is the number of sampled points during the move. Note that the representative patient data shows that from admission to discharge these numbers become less negative, indicating that the patient contributed more force and motion to complete the task.

The kinetic measurement for PM3 is the average absolute power normal to the target axis (PM3a—borrowing the term from electrical engineering, PM3a is similar to "Reactive Power"), and the kinematic measurement is the root-mean-square deviation normal to the target axis (PM3b).

$$\text{PM3a} = \frac{1}{N}\sum_{i=1}^{N}|F_x(i)\dot{x}(i)| \tag{9}$$

$$\text{PM3b} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}x(i)^2} \tag{10}$$



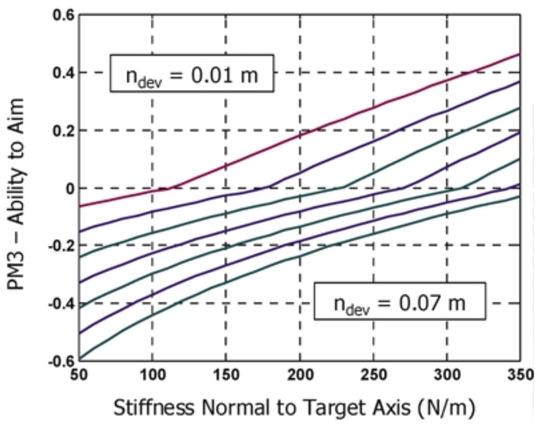


Figure 6. Performance indices: Calibration curves from simulation.

where F_x is the force normal to the target axis. Both measures for PM3 show that the patient's ability to aim improved between admission and discharge.

Simulations of a two-link human arm interacting with a robot using the novel impedance controller were conducted to determine how the performance measures varied with the desired range of robot command variables and assumed patient variation. The controller time allotted for a move from the starting position to the desired target was varied between 1.5 and 4.5 seconds. To assist patients with their aim, the stiffness of the impedance controller was varied from 50 to 350 N/m. It was also assumed that the patients' simulated move time, T_a, would lie in between 1.5 and 4.5 seconds, and the maximum deviation along the normal to the target axis on a curved trajectory, n_{dev}, would be between 0.01 and 0.07 m.

The final selections for PM2 and PM3 are displayed in Fig. 6. PM2, the ability to move, is defined as a weighted sum of PM2a and PM2b. Thus, both kinetic and kinematic information of the patient's move are contained in this performance measure. In particular, the positive values represent the average deviation from the commanded minimum jerk trajectory when the patient is moving ahead of the assist, and the negative values represent the average power delivered from MIT-MANUS to the patient during assisted moves. By design, this composite performance measure was able to distinguish patients who were capable of moving to the target in the specified time from those who were not. A purely kinetic measurement was unable to discriminate between subjects who moved ahead of the robot assist because the robot was back-drivable. Similarly, a purely kinematic measurement was unable to discriminate between patients who required assistance because the stiffness of the impedance controller kept the patient close to the minimum jerk trajectory. PM3, on the other hand, is defined solely as a function of PM3b, the RMS normal deviation of the patient.

Several observations can be made concerning PM2 and PM3. As the control parameters increase, the performance measures also increase monotonically along each line of constant patient parameters. Note, when PM2 equals zero, the patient move time equals the commanded robot move time, and when PM3 equals zero, each value of maximum patient normal deviation corresponds to a value of controller stiffness. MIT-MANUS is able to track the patient's move time by using a simple control law such as:

$$t_m[J+1] = t_m[J] + \lambda \cdot \text{PM2}[J] \tag{11}$$

where t_m $[J]$ is the controller move time during the J game, and λ is the gain from PM2 to t_m.

This tracking algorithm is a good first step, but we are not simply interested in tracking the patients' performance, but intend to challenge them to improve their performance or, at the very least, motivate them to maintain it. During the initial m (out of M) games, the control system operates in a tracking mode to identify how well the patient is able to complete the task. Recall, when the controller parameters are changed, the zero PM values occur at different levels of patient performance. In order to help account for this, a secondary performance measure will be introduced that serves as an indication of patient variability. The performance level (PL) is defined to be

$$\mathrm{PL} = \left\{ \begin{array}{c|c} -1 & \mathrm{PM} < -0.01 \\ 0 & -0.01 \leq \mathrm{PM} \leq 0.01 \\ +1 & \mathrm{PM} > 0.01 \end{array} \right\} \quad (12)$$

The value of PL indicates whether patients perform worse ($\mathrm{PL} = -1$) or better ($\mathrm{PL} = 1$) than their expected ability at $\mathrm{PM} = 0$. $\mathrm{PL} = 0$ denotes when patients perform approximately the same.

The last M-m games in a session are grouped into sections of 3 games each. During each of these sections, the desired controller move time and the controller stiffness remain constant. By considering the average PM values and the sum of the PL values ($-3 \leq \mathrm{PL}_{\mathrm{sum}} \leq 3$) during the three games, the controller adapts to patients' performance and variability, and challenges them to continue to improve. The proposed performance-based adaptive algorithm is stated as follows:

$$t_m|_{J+1,J+2,J+3} = t_m[J] + \lambda \cdot \alpha(\mathrm{PL}_{\mathrm{sum}}) \cdot \mathrm{PM2}_{\mathrm{ave}}$$

where

$$\alpha(\mathrm{PL}_{\mathrm{sum}}) = \left\{ \begin{array}{l|l} 0.5 & \mathrm{PL}_{\mathrm{sum}} = -3 \\ 0.25 & \mathrm{PL}_{\mathrm{sum}} = -2 \\ 0.125 & \mathrm{PL}_{\mathrm{sum}} = -1 \\ 0.125 & \mathrm{PL}_{\mathrm{sum}} = 0 \\ 0.25 & \mathrm{PL}_{\mathrm{sum}} = +1 \\ 0.5 & \mathrm{PL}_{\mathrm{sum}} = +2 \\ 1 & \mathrm{PL}_{\mathrm{sum}} = +3 \end{array} \right\} \quad (13)$$

The desired effect of challenging patients to improve while keeping them motivated is accomplished, in part, by the asymmetry in the definition of $\alpha(\mathrm{PL}_{\mathrm{sum}})$. When patients do consistently better than their previous performance, $\alpha(+3) = 1$, and when patients do consistently worse, $\alpha(-3) = 0.5$. Thus, the algorithm uses information related to patient variability to dictate how much of an increase or decrease of the parameter there will be during the next 3 games. The asymmetry challenges improving patients to improve further, but makes the task easier, to a lesser extent, when patient performance is worsening.

So far, we have discussed only the approach to modify the time for movement completion. An analogous approach is used to alter the stiffness normal to the target axis. The only difference is the selection of λ, the gain from PM3 to k.

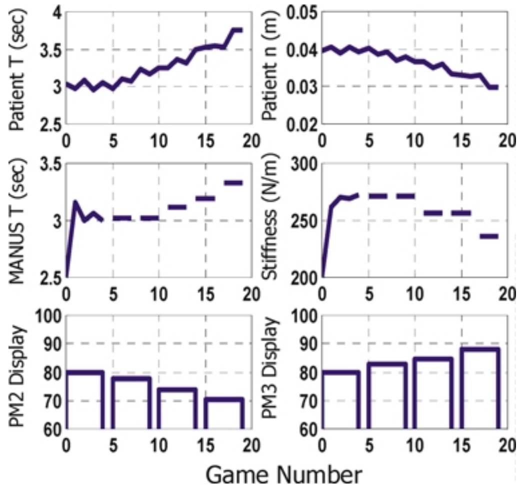


Figure 7. Simulation of the adaptive algorithm for a therapy session lasting for 20 repetitions.

Figure 7 displays a hypothetical case of a therapy session lasting 20 games. The first row is the patient simulation movement parameters, the second row is for the progressively changing control parameters, and the third row displays the PM2 and PM3 values that would be displayed to the patient after games 5, 9, 14, and 19. In this session, a (simulated) patient tries to improve his/her aiming skills, but, as a result, moves more slowly. Since the performance has improved with respect to aim, the controller stiffness is decreased, providing less guidance and challenging him/her to further improve. Although the patient's preferred move time has slowed to almost 3.8 seconds, MIT-MANUS completes the move in approximately 3.4 seconds. Therefore, the algorithm allows the patient to slow down from the original performance, but attempts to motivate the patient to do better than the current performance. The height of the bar graph displays for PM2 and PM3 are given as percentages and are defined as:

$$\mathrm{PM\%} = \left\{ \begin{array}{c} 80 \text{ After Game } 4 \\ 80 + c_1 \sum \mathrm{PL} + c_2 \mathrm{PM}_{\mathrm{ave}} \end{array} \right\} \quad (14)$$

In this expression, c_1 and c_2 are scaled to limit patient display between approximately 70 and 90% as the robot parameters are changed. Recall that the purpose of the visual display is to provide positive reinforcement to the patient throughout the session.

The last of the performance measures is PM4. It records the maximum distance reached away from the workspace origin during a particular move. Its complement is the distance from the robot position to the target position at the maximum distance reached.

The algorithm is currently being tested at the Burke Rehabilitation Hospital, Helen Hayes Rehabilitation Hospital, and Baltimore Veterans Administration Medical Center. As mentioned earlier, in addition to the algorithm challenging the patient to improve, a bar graph is displayed every five games in an attempt to keep the patient motivated and interested in the therapy session (Krebs et al., 2001a, 2001b). Four bars are displayed to report how well the subject can initiate movement, move to the targets, aim along the target axes, and reach the target position in the allotted time. Using shaping techniques commonly adopted in learning studies to assert error free performance (e.g., therapy to reduce speech impairment (Merzenich et al., 1996)), the displays are appropriately scaled such that the subjects nominally score between 70 and 90 percent as the robot parameters are changed. This rewards the subjects' effort and provides them with motivation to further improve their performance.

Discussion

The fundamental mechanisms underlying neuro-recovery are understood poorly at best. A prominent theme of current neuroscience research into the sequelae of brain injury posits that activity-dependent plasticity underlies neuro-recovery. Plasticity may be due to the unmasking of pre-existing connections, activity-dependent synaptic changes, or neosynaptogenesis, the growth of new connections. Experimental support for this idea derives primarily from measurements of synaptic branching and cortical thickness in rats raised in enriched and deprived environments (e.g., Diamond et al., 1987, 1976, 1985, 1966; Greer et al., 1982) and in monkeys recovering from ischemic injury (e.g., Nudo et al., 1996). One challenge is to understand whether the neurobiological mechanism for the changed motor behavior is based on reorganization of normal cortex tissue adjacent to the injured tissue, or of more distant supplemental motor circuits (in the supplemental motor area, the basal ganglia, or cerebellum), or of the unaffected hemisphere (Jenkins and Merzenich, 1987; Jones and Shallert, 1994; Aizawa et al., 1994). Another (and probably related) mechanism involves assumption of lost function by adjacent areas of undamaged brain tissue. Reorganization of cortical maps has been demonstrated in the motor system (Asanuma, 1991; Jacobs and Konoghue, 1991), sensory system (Merzenich et al., 1984; Pons et al., 1988), visual system (Kaas et al., 1990), and auditory system (King and Moore, 1991). A further mechanism of recovery of function post stroke involves the homologous regions of the unaffected contralateral cerebral hemisphere substituting for the infarcted brain tissue (Fisher, 1992; Glees, 1980; Sabatini et al., 1994). A mechanism by which motor function may be controlled by the unaffected ipsilateral hemisphere may be through the 25% of pyramidal tract fibers that are uncrossed (Nyberg-Hansen and Rinvik, 1963). Activity-dependent cortical plasticity has been found to accompany motor learning; rehabilitation and training after injury have also been reported to influence the pattern of re-organization. Timing of the stimulus during training is also an issue. Recent results with TMS (Transcranial Magnetic Stimulation) timed with electrical stimulation to the motor point of the FDI (first dorsal interosseous muscle) to determine the excitability of the cortical projection suggested that proper timing leads to an increase in size and excitability of the corticospinal projection. The reverse is also true: improper timing has a negative effect (Classen et al., 1998; Stefan et al., 2000; Ridding et al., 1995).

The novel performance-based progressive algorithm provides a mechanism for a patient to evolve from hemiplegic to normal arm movement. Like a line integral, it specifies the initial and final conditions (PM1 and PM4) and the path between these conditions (PM2 and PM3). PM1 is particularly useful for hemiplegic or severe hemiparetic patients as they recover some movement. It requires the patient to actively participate in the initiation of movement guaranteeing proper timing between afferent-efferent signals to induce increase in the excitability of the corticospinal projections (speed or EMG threshold). It might be also used to train the recruitment of a particular muscle group. PM4 is useful for patients with either severe or moderate hemiparesis. It rewards patients for relaxing their arms, which might allow the impedance controller to drive their hands closer to the target (reduce tone—severe case), or it measures patients' ability to move to the target ahead of the controller. For patients with moderate or mild hemiparesis, PM2 and PM3 provide a speed-accuracy tradeoff.

The concept of using EMG to trigger the operation of another device is at least 50 years old. Norbert Wiener proposed the concept of an EMG-Controlled prosthetic arm in his well-known work "Cybernetics." Several researchers implemented this concept in different arm prostheses like the Boston-Utah and Waseda arm (Hogan, 1976; Philipson, 1985; Kato et al., 1967; Akazawa et al., 1983). EMG signals were also proposed in exoskeletal devices to augment the human strength (Kazerooni, 1990; Rosen et al., 2001) and as pattern classification (Graupe, 1983; Fukuda et al., 1998; 2003; Peckham, 1980; Triolo, 1985). EMG has also been used to study muscle activities in normal subjects (Mussa-Ivaldi et al., 1985) and in the disabled (Reinkensmeyer et al., 1999; Lum et al., 2000; Kearney and Mirbagheri, 2001; Mirbagheri et al., 2001; Dewald et al., 1995; Cozens, 1999). Nevertheless, to our knowledge, nobody prior to our work suggested its application to trigger robot-assisted therapy.

Although more subjects are needed to make a firm statement about the effectiveness of the algorithm (approximately 20 have completed the therapy protocol to date), the therapists administering the treatment have already noted one very strong and somewhat unexpected benefit of the new therapy, a reduction in arm spasticity and tone. Spasticity is a neurological condition causing an abnormal increase in muscle tone that occurs when the muscle is stretched. In a single session, comparing patient at the beginning and end of the therapy activity, the therapists noted an "in-your-face" significant reduction of tone. Other modalities of robotic therapy tend to increase spasticity or keep it constant.

Conclusion

In this paper we have presented a novel algorithm that, in the best tradition of motor learning, maximizes the chances to deliver optimal therapy. It continuously engages the patient in the activity, while respecting purported timing to increase in size and excitability of the corticospinal projection. It regulates the speed-accuracy tradeoff while taking an errorless approach.

Naturally the desired outcome of rehabilitation is not merely a reduction of impairment, but an improvement in functional abilities and participation in daily life tasks. Currently, robot-assisted therapy is primarily administered in isolation from other rehabilitation efforts, with little emphasis on the practice of trained movements during daily functional tasks. Research studies have indicated that the use of imagery-based tasks and the presence of objects during goal-directed tasks can significantly enhance movement kinematics during reach, in persons with and without CVA (Wu et al., 1998). Therefore we are in the process of integrating the performance-based progressive algorithm into functional tasks. We are developing a therapeutic practice model that 1) uses imagery-based, simulated tasks during robotic therapy sessions implemented with the same performance-based progressive therapy and 2) is directed toward the carryover of robot-trained movements during functional activities. At the same time, to augment the potential of robot-assisted neuro-rehabilitation, we are developing additional robots to work with different muscles and limb segments, e.g., spatial motion, wrist, fingers, and legs (Jugenheimer et al., 2001; Buerger et al., 2001; Williams et al., 2001; Krebs et al., 2002; Celestino et al., 2003). The intent is that this functionally-based robotic therapy may improve the generalization of learned/recovered motor skills, and thereby enhance functional motor performance and reduce impairment of those who matter: stroke survivors.

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Notes

1. Industrial robots can be programmed to follow different paths *or* exert different forces, but not both simultaneously. Only robots designed specifically to be interactive (i.e., backdriveable) can be programmed to deliver interactive therapy and different force field patterns (active, semi-active, passive, resistive) including patterns that are non-existent in nature.
2. Conceived in the early 1980's by one of the co-authors (Neville Hogan), Impedance Control has been applied successfully in numerous robot applications including human-motor interaction (Hogan, 1985). It has been extensively adopted by other robotics researchers concerned with human-machine interaction (see, e.g., the February 1997 issue of IEEE Control System, Special Issue on Robotics, which contains several articles on impedance control).

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