Proceedings of the 29th Annual International
Conference of the IEEE EMBS
Cité Internationale, Lyon, France
August 23-26, 2007.

A Computational Model of Human-Robot Load Sharing during Robot-Assisted Arm Movement Training after Stroke

David J. Reinkensmeyer, *Member, IEEE,* Eric Wolbrecht, James Bobrow, *Member, IEEE*

Abstract— An important goal in robot-assisted movement therapy after neurologic injury is to provide an optimal amount of mechanical assistance to patients as they complete motor tasks. This paper presents a computational model of how humans interact with robotic therapy devices for the task of lifting a load to a desired height. The model predicts that an adaptive robotic therapy device will take over performance of the lifting task if the human motor control system contains a slacking term (i.e. a term that tries to the reduce force output of the arm when error is small) but the robot does not. We present experimental data from people with a chronic stroke as they train with a robotic arm orthosis that confirms this prediction. We also show that incorporating a slacking term into the robot overcomes this problem, increasing load sharing by the patient while still keeping kinematic errors small. These results provide insight into the computational mechanisms of human motor adaptation during rehabilitation therapy, and provide a framework for optimizing robot-assisted therapy.

I. Introduction

There has been increasing interest over the past decade in using robotic devices to assist in movement training of the arms, hands, and legs following stroke [1]. The predominant robot control paradigm that has been implemented to date is what clinicians refer to as "active assistance". In this paradigm, a therapist or robotic device provides mechanical assistance to the patient to help complete a desired movement, but only as much as is needed. The rationale for this approach can be summarized by what might be called the "assist-as-needed hypothesis":

Providing too much assistance will cause the patient to decrease efferent output, which will decrease use-dependent neuroplasticity. On the other hand, providing too little assistance will reduce range of motion and afferent input, limit the number of movement repetitions that the patient achieves, and in some cases make accomplishment of the desired motor task impossible, causing frustration, decreasing motivation for training, and again reducing plasticity.

According to this hypothesis, then, providing the right amount of assistance is essential for optimizing training.

Several controllers for robotic therapy devices have been designed with the assist-as-needed hypothesis in mind. The first controllers used proportional position feedback controller to provide assistance-as-needed, as such controllers increase force as kinematic error increases [2, 3]. Other controllers have taken the approach of automatically triggering robotic assistance based on a measurement of position error or of a delay in time-to-complete the desired task [4, 5]. Strategies have been proposed to iteratively adapt the stiffness, timing, desired trajectory, or forces of the robot as a function of real-time measurement of the patient's performance of the task [6-11].

It has not yet been possible to base the control laws for robotic assistance on a mechanistic understanding of how the human motor system interacts with a robotic therapy device during rehabilitation therapy. Perhaps the work that has been nearest to achieving this goal is recent work from our group that showed how the problem of providing assistance-as-needed could be posed as an optimization problem [12]. We then solved for the optimized assistance-as-needed controller for a walking task. However, this study examined how unimpaired people adapted to a robotic force field, rather than how people with a neurologic impairment participated in a real rehabilitation task.

Here we develop a computational model of how people with weakness interact with a robotic therapy device for a real rehabilitation task: lifting a load to a desired height. We then use the model to gain insight into designing a controller that assists-as-needed. We present experimental data from eight people with a chronic stroke who trained with a robotic arm orthosis that confirms the model's predictions.

II. Computational Model of Human-Robot Loading Sharing

A. Model Definition

Consider a therapy task in which the patient is instructed to lift his or her arm to a height $x = x_d$ with the assistance of a robot. We wish to predict how the percentage of the load that the patient lifts depends on the robot's behavior.

We assume that the dynamics of this task can be linearized when x is near x_d, so:

$$M\ddot{x} + B\dot{x} = -W + u + R \qquad (1)$$

where M and B are the combined mass and damping of the patient's arm and the robot, W is the weight of the patient's arm, u is the vertical lifting force from the patient's muscles expressed in hand coordinates, and R is the vertical assisting force from the robot expressed in hand coordinates. Define the position error as $e = x - x_d$. We hypothesize that the

Manuscript received April 13, 2007. This work was supported by NIH N01-HD-3-3352 and NCRR M01RR00827.

D. J. Reinkensmeyer, E. A. Wolbrecht, and J.E. Bobrow are with the Department of Mechanical and Aerospace Engineering, University of California at Irvine, 92617-3975 (dreinken@uci.edu)

human controller for this task is of the form:

$$\dot{u} = -k_h \dot{e} - g_h e - f_h u \quad (2)$$

This controller has three terms that model known aspects of human motor behavior. The first term is a proportional position control term with stiffness k_h. This term corresponds to the well-known spring-like impedance of human limbs, which arises due to muscle mechanics and segmental reflexes. The second term is an integral position control term with gain g_h. This term acts like an error-based adaptive controller that forms an internal model of the forces required to lift the arm to the target: if there is a persistent error e, then this term causes the controller to increase its output to reduce this persistent error, stopping when u = W and e = 0. The third term is a slacking (or "forgetting") term with a forgetting rate $f_h \geq 0$. Recent studies of human motor adaptation to novel force field environments have observed the presence of such a term in models of the human controller [13]. The model presented here incorporates slacking in a continuous-time formulation for the first time. The effect of this slacking term is to cause an exponential decay in the human force output $u = u_0 e^{-t/\tau_h}$ with a time constant $\tau_h = 1/f_h$ when position error is small.

A key prediction of this model of human motor control is that the force output of the human and the position error will be linearly related in the steady state:

$$u = -(g_h / f_h) e \quad (3)$$

Note that this relationship should apply regardless of the way that the robotic therapy device assists in the lifting task.

B. Robot Controller and Human/Robot Closed Loop Dynamics

Now, consider robotic therapy devices that use a control law that is similar to the form of the human control law to provide assistance for the lifting task:

$$\dot{R} = -g_r e - k_r \dot{e} - k_D \ddot{e} - f_r R \quad (4)$$

where R is the vertical assisting force from the robot, g_r is the integral gain, k_r is the proportional gain (robot stiffness), k_d is the damping, and f_r is the robot forgetting rate. This control law can be used to approximate a range of possible control laws for robotic therapy devices by varying the gains, including a standard adaptive controller, as we show below.

Given the models of the human and robot controllers, we would like to answer two questions of particular interest:

1) What is the position tracking error that the interacting patient and robot controllers achieve?

2) What is the % of arm weight that the patient supports?

Within a rehabilitation framework guided by the active assistance hypothesis, we desire the position error to be small and the percentage of arm weight that the human supports to be large for maximal therapeutic benefit.

C. Model predictions of steady-state behavior

We now examine what the model predicts for steady-state behavior for three special cases.

Case 1: Robot does not slack, patient does

The first case is when the robot does not contain the slacking term, but the human controller contains both the integral and slacking terms. Substituting $f_r = 0$ into Eq. 3 and solving for the steady state we find:

$$e = 0 \quad and \quad u = 0$$

Thus, the model predicts that the tracking error will be zero, and that the robot will fully support the arm. Essentially, the robot controller integrates position error, eliminating the error, and the human adaptive controller allows the robot to "take over" the task because of its slacking property.

Case 2: Robot and patient slack

Now consider the case in which both the human and the robot slack. In the steady state the tracking error and load supported by the human are:

$$e = \frac{-W}{g_h / f_h + g_r / f_r} \quad and \quad \frac{u}{W} = \frac{A}{1 + A} \quad where \ A = \frac{g_h / f_h}{g_r / f_r}$$

Note that tracking error is small if g_r/f_r and/or g_h/f_h are large, while the load sharing depends on their ratio A. If we design the robot so that $g_r/f_r \ll g_h/f_h$ and the patient's motor control system has the property that $g_h/f_h \gg 0$, then

$$e \approx 0 \quad and \quad u \approx W$$

This result is what we desire of the robotic training system: the error is small and the patient lifts the weight. Note that we can make g_r/f_r small by making the robot slacking rate f_r large (i.e. incorporate enough robot slacking).

We have assumed so far that the patient can lift the weight of his arm. When the maximum force that the patient can generate is limited ($u_{max} < W$), the robotic controller with slacking will cause u to approach u_{max} (with the closeness dependent on g_r/f_r and g_h/f_h) and the tracking error will be:

$$e = -f_r / g_r \left(W - u_{max} \right)$$

Thus, with this controller, the robot creates the residual force R necessary to make the tracking error small when the patient is weak, if g_r/f_r is sufficiently large.

Based on the analysis of Case 1 and Case 2, we state the following model predictions:

Model Prediction 1: If the robot has an integral control term but does not incorporate slacking, then tracking error will be zero and the robot will take over the lifting task.

Model Prediction 2: Incorporating robot slacking will keep tracking error small but cause the patient to perform significantly more of the task.

Case 3: Human slacks, robot is position-controlled

A third interesting case is when the robot does not incorporate integral or forgetting terms ($g_r = 0$, $f_r = 0$), but operates with proportional position control ($k_r > 0$). This case approximates the situation with most existing robotic therapy devices, which drive the patient's limbs through a desired movement using proportional position feedback control. We assume the human controller still incorporates slacking ($f_r > 0$). In this case we find:

$$e = \frac{-W}{g_h / f_h + k_r} \quad and \quad \frac{u}{W} = \frac{A}{1+A} \quad where \;\; A = \frac{g_h / f_h}{k_r}$$

Thus, the human always lifts less than W, with the load sharing determined by the ratio of g_h/f_h to k_r. If $k_r >> g_h/f_h$ and k_r is large then

$$e \approx 0 \quad and \quad u \approx 0$$

and the model predicts that the human will not lift any of the load. If $k_r << g_h/f_h$ and g_h/f_h is large and $u_{max} > W$ then:

$$e \approx 0 \quad and \quad u \approx W$$

and the model predicts that the patient will lift the full load. The amount of patient participation in the lifting task depends on the robot stiffness k_r relative to the human parameter g_h/f_h. We found below in experiments with two chronic stroke subjects that the parameter g_h/f_h was large (> 4000 N/m). Thus, we make the following prediction:

Model Prediction 3: Patients will exert effort in completing the task even when aided by a position controlled robot with moderate stiffness, but this effort will be less than when assisted by a more compliant robot.

We performed experiments to test the first two model predictions. We have not tested the third prediction yet.

III. Experimental Methods

A. Robotic Therapy Device

The robotic orthosis we used to test these hypotheses is called "Pneu-WREX" [11, 14](Fig. 1). It is a 4 degrees-of-freedom robot based on a passive arm support called WREX, developed for children by Rahman et al. [15]. 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 [11]. 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 redundant hardware and software safety features.

B. Active-assist controller

To control Pneu-WREX as it interacted with the patient's arm, we implemented an adaptive controller, which is described in detail in [16]. Briefly, the controller calculates the force R that the robot applies to the arm using an adaptive feedforward term $\hat{a}$ that estimates the extra force needed to lift the patient's arm (i.e. the force besides what the patient is generating), and proportional and derivative position feedback terms:

$$R = \hat{a} - k_P e - k_D \dot{e} \qquad (5)$$

The term $\hat{a}$ is estimated with a parameter update law:

$$\dot{\hat{a}} = -f_r \hat{a} - \Gamma^{-1}\left(\dot{e} + \Lambda e\right) \qquad (6)$$

where Γ and Λ are positive gains used in the adaptive controller. The parameter f_r is the slacking rate, which is a novel modification that we made to the conventional adaptive control update law, in order to make the robot attempt to reduce its force when tracking is small [16]. Combining the controller and adaptive update laws gives:

$$\dot{R} = -g_r e - k_r \dot{e} - k_D \ddot{e} - f_r R \qquad (7)$$

where $g_r = f_r k_p + \Gamma^{-1}\Lambda$ and $k_r = k_p + \Gamma^{-1} + f_r k_D$. Eq. 7 is identical to the equation assumed for the robot controller in the computational model (i.e. Eq. 3).

Fig. 1. Person with a stroke participating in movement training with a robotic exoskeleton called Pneu-WREX. This pneumatic robot allows motion of the arm in four degrees-of-freedom (DOF). The robot allows the hand to reach a wide range of points in 3D space, but with the forearm always horizontal. The device allows a small amount of shoulder translation forward and backward.

C. Experimental Protocol

The University of California Institutional Review Board approved all experiments and the subjects provided informed consent. We tested how eight chronic (> 6 months after stroke) interacted with the adaptive controller with and without the slacking term). For these experiments, the proportional gain of the robot arm, k_p, was set to 70 N/m.

In one experiment we asked the subjects to follow a minimum jerk trajectory with a peak velocity of 0.12 m/sec from a central home position to seven targets spaced across a frontal plane in front of the subject. In another experiment, we instructed the subjects 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 (also with peak velocity of 0.12 m/sec). The targets were spaced 30 cm apart in the horizontal plane at chest level approximately 45 cm in front of the body.

IV. Results

A. The compliant robot successfully assisted in reaching

Figure 2 shows that the robot controller learned to assist patients with a range of severity of motor impairment in reaching to the 7 targets that were placed in different areas of the workspace, even when the targets were not reachable without robotic assistance. The reaching trajectories exhibited substantial variability because the robot was mechanically compliant.

Figure 2 also displays the mean magnitude of the assistive force provided by the robot as a horizontal bar, with slacking (the slacking time constant $\tau = 1/f_r$ was 10 s) and without slacking ($\tau = \infty$) incorporated into the controller. The reaching trajectories were similar with and without slacking, but the assistive force provided by the robot was smaller with robot slacking, consistent with Model Prediction 1.

B. *Load sharing depended on robot slacking*

To quantify the load sharing more precisely, we asked the subjects to raise their arms and then move between two targets at shoulder height, spaced 30 cm apart in the frontal plane. Figure 3 illustrates the mean of the vertical robot assistance force and the vertical tracking error after 20 back-and-forth movements as a function of the impairment severity of the subject. When the robot controller did not contain a slacking term (i.e. $\tau = \infty$), the mean tracking error was small, but the robot eventually lifted 100% of the weight of the arm, even though the robot assistance force was initialized to zero. With a slacking term ($\tau = 10$ s), the robot lifted significantly less of the weight of the arm (paired t-test, $p < 0.01$). The robot contribution to the load sharing increased with increasing impairment severity, as would be expected since more severely impaired patients had less strength to lift their arms. Tracking errors also increased when the robot incorporated slacking, but were still relatively small (less than 2 cm). This experiment confirmed Model Prediction 1 – i.e. that the robot will take over the lifting task if the robot does not incorporate slacking, as well as Model Prediction 2 – i.e. that incorporating robot slacking will cause the patient to lift significantly more of the load while keeping error small.

C. *Validity of the slacking-model of human motor control*

We tested how well the model of human motor control defined by Equation 2 fit the experimental data in the steady state for two subjects. We asked the subjects to perform the two-target tracking task as we varied the robotic slacking time constant (i.e. $\tau = 1/f_r$) through a wide range. The steady state tracking error and assistance force varied as the robot slacking factor varied. The two were linearly related, as predicted by Eq. 3 (subject 1: Fugl-Meyer score = 53, r^2 = 0.84, $p < 0.001$; subject 2: Fugl-Meyer score = 31, $r^2 = 0.53$, $p = 0.06$). The slope of the line was g_h/f_h = 4300 N/m for subject 1, and 6244 N/m for subject 2.

V. Discussion and Conclusion

This paper presents a computational model of how humans interact with a robotic therapy device for the task of lifting a load to a desired height. The model includes terms that model human limb stiffness, adaptive formation of an internal model (implemented simply with an integral control term), and a slacking process in which the motor control system attempts to reduce its effort when error is small. The model predicts that the human will relinquish performance of the lifting task to an adaptive robot if the human

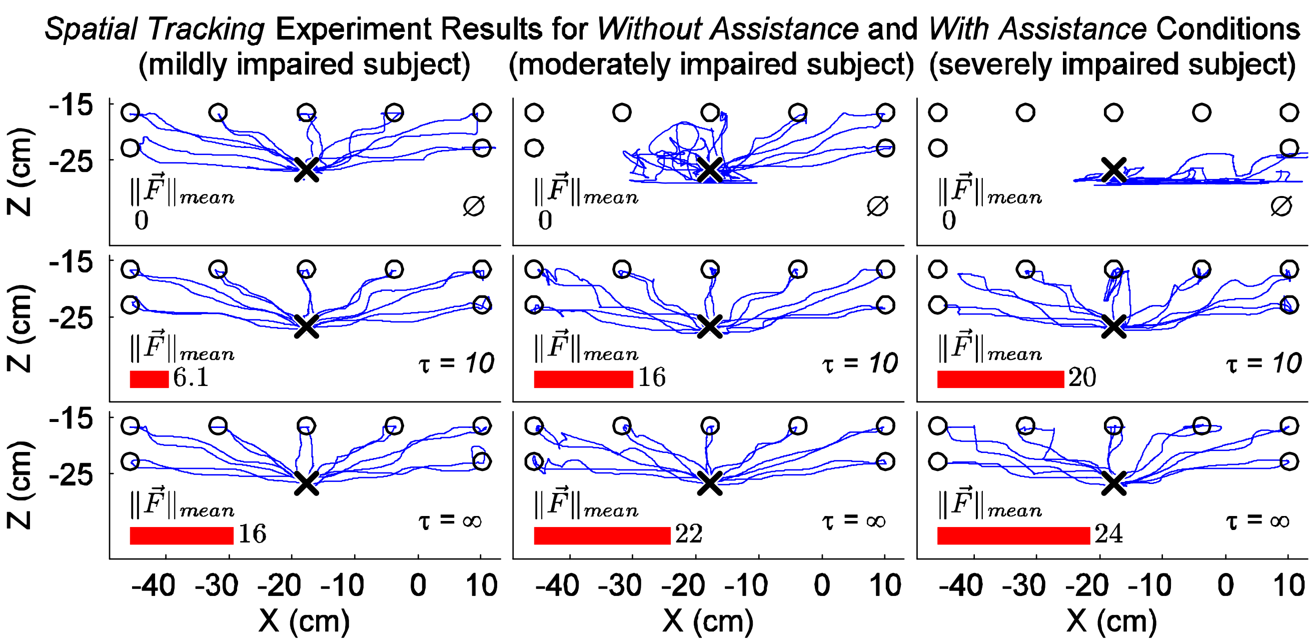

Figure 2: Reaching trajectories in the frontal plane, viewed from behind the subject, with and without robot assistance. Each column represents a different, left hemi-paretic subject reaching with the left arm. The first row shows the reaching trajectory without robot assistance. The second row shows the reaching trajectory with robot assistance, when the robot assistant incorporated a slacking time constant $\tau = 1/f_r$ of 10 seconds. The third row shows the reaching trajectory when the robot did not incorporate a slacking time constant (i. e. $f_r = 0$). The horizontal bars in the bottom two rows show the mean magnitude of the force the robot applied over time in order to assist the subjects in reaching. The robot helped the patients to reach the targets with less force when it incorporated slacking.

controller contains a slacking term but the robot does not. Experimental

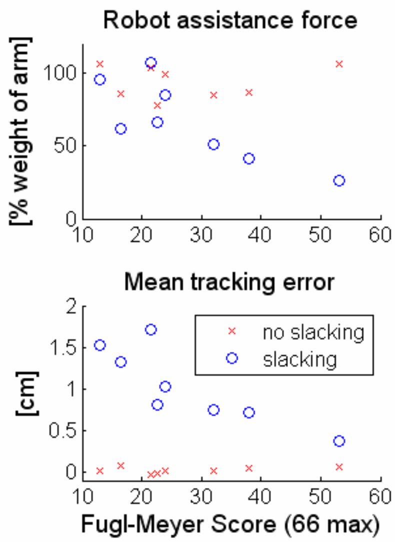

Figure 3: Mean robot assistance force and vertical tracking error measured while eight stroke subjects performed a tracking task with the arm. Means were taken following 20 back and forth movements by the subjects with the robot assisting. The robot assistance was initialized to zero on the first movement. A Fugl-Meyer score of 0 corresponds to complete paralysis, while a score of 66 corresponds to normal movement ability. Note that the robot lifted 100% of the arm weight if its controller did not contain a slacking factor (x), and assisted less when its controller included a slacking factor (o).

data from individuals with a chronic stroke confirmed this prediction. Incorporating a slacking term into the robot overcame this problem, as predicted by the model, increasing load sharing by the subjects while keeping errors small.

These results provide a computational basis for optimizing robotic therapy in accordance with the assistance-as-needed hypothesis. On the modeling side, future work will examine how well the transient response predicted by the model fits experimental data. On the clinical testing side, we plan on rigorously testing the assistance-as-needed hypothesis by training one group of patients with a robot slacking factor, and one group without it.

Previous robotic therapy devices have typically used position feedback control with a moderate stiffness to assist patients in moving their limbs. The model presented here predicts that the patient will stay actively involved in such a situation, but with somewhat reduced participation. The participation will be greater if the robot stiffness is small compared to the parameter g_h/f_h (i.e. Model Prediction 3), however, decreasing k_r limits the robot's ability to help the patient complete desired movements. We found g_h/f_h to be large (> 4000 N/m) for two stroke subjects. Israel et al. [17] recently found that people with a spinal cord injury who walked in a position-controlled Lokomat robotic gait orthosis with the instruction to "follow along" used about 60% less energy (measured by oxygen consumption) than when they were manually assisted by therapists, consistent with the prediction of the model presented here. Given g_h/f_h, the model predicts the proportion of load the human will carry as a function of the robot stiffness, and thus is experimentally falsifiable.

We conclude with the following observation: if the desire is to keep the robot very compliant, the mean tracking errors small, and the patient involved, then incorporating a slacking term into a compliant robot controller that adaptively forms a real-time model of the patient's weakness is an effective way to achieve these goals.

References

[1] D. Reinkensmeyer, J. Emken, and S. Cramer, "Robotics, motor learning, and neurologic recovery," Annual Review of Biomedical Engineering, vol. 6, pp. 497-525, 2004.

[2] P. S. Lum, D. J. Reinkensmeyer, and S. L. Lehman, "Robotic assist devices for bimanual physical therapy: preliminary experiments," IEEE Transactions on Rehabilitation Engineering, vol. 1, pp. 185-191, 1993.

[3] H. I. Krebs, N. Hogan, M. L. Aisen, and B. T. Volpe, "Robot-aided neurorehabilitation," IEEE Trans Rehabil Eng, vol. 6, pp. 75-87., 1998.

[4] L. E. Kahn, M. L. Zygman, W. Z. Rymer, and D. J. Reinkensmeyer, "Robot-assisted reaching exercise promotes arm movement recovery in chronic hemiparetic stroke: A randomized controlled pilot study," Journal of Neuroengineering and Neurorehabilitation, vol. 3:12, 2006.

[5] C. Takahashi, L. Der-Yeghiaian, V. H. Le, and S. C. Cramer, "A robotic device for hand motor therapy after stroke," Proceedings of the 2005 IEEE International Conference on Rehabilitation Robotics, June 28-July 1, Chicago, Illinois, pp. 17-20, 2005.

[6] H. Krebs, J. Palazzolo, L. Dipietro, M. Ferraro, J. Krol, K. Rannekleiv, B. Volpe, and N. Hogan, "Rehabilitation robotics: performance-based progressive robot-assisted therapy," Auto. Rob., vol. 15, pp. 7-20, 2003.

[7] L. Kahn, P. Lum, W. Rymer, and D. Reinkensmeyer, "Robot-assisted movement training for the stroke-impaired arm: Does it matter what the robot does?," J Rehab Res and Dev, vol. 43 pp. 619-630 2006.

[8] R. Riener, L. Lunenburger, S. Jezernik, M. Anderschitz, G. Colombo, and V. Dietz, "Patient-cooperative strategies for robot-aided treadmill training: first experimental results," IEEE Trans Neural Sys & Rehab Eng, vol. 13, pp. 380-394,, 2005.

[9] J. L. Emken, J. Beres-Jones, S. J. Harkema, C. Ferreira, and D. J. Reinkensmeyer, "Feasibility of manual teach-and-replay and continuous impedance shaping for robotic locomotor training following spinal cord injury," to appear, IEEE Trans on Biomedical Engineering, 2007.

[10] D. Aoyagi, W. E. Ichinose, S. J. Harkema, D. J. Reinkensmeyer, and J. E. Bobrow, "A robot and control algorithm that can synchronously assist in naturalistic motion during body weight supported gait training following neurologic injury," to appear, IEEE Trans Neural Syst and Rehab Eng, 2007.

[11] E. Wolbrecht, J. Leavitt, D. Reinkensmeyer, and J. Bobrow, "Control of a pneumatic orthosis for upper extremity stroke rehabilitation," IEEE Eng in Med and Biol Conf, New York, pp. 2687 – 2693, 2006.

[12] J. Emken, R. Benitez, and D. Reinkensmeyer, "Human-robot cooperative movement training: learning a novel sensory motor transformation during walking with robotic assistance-as-needed," Journal of Neuroengineering and Rehabilitation, vol. 4, pp. 8, 2007.

[13] J. L. Emken, R. Benitez, A. Sideris, J. E. Bobrow, and D. J. Reinkensmeyer, "Motor adaptation as a greedy optimization of error and effort," Journal of Neurophysiology 97(6):3997-4006, 2007.

[14] R. Sanchez, E. Wolbrecht, R. Smith, J. Liu, S. Rao, S. Cramer, T. Rahman, J. Bobrow, and D. Reinkensmeyer, "A pneumatic robot for re-training arm movement after stroke: rationale and mechanical design," IEEE Int Conf on Rehab Robotics, Chicago, IL, vol. 500-504, 2005.

[15] T. Rahman, W. Sample, and R. Seliktar, "Design and testing of WREX," Lecture notes in control and information sciences, pp. 243-250.

[16] E. T. Wolbrecht, V. Chan, V. Le, S. C. Cramer, D. J. Reinkensmeyer, and J. E. Bobrow, "Real-time computer modeling of weakness following stroke optimizes robotic assistance for movement therapy," IEEE Conference on Neural Engineering, to appear, 2007.

[17] J. F. Israel, D. D. Campbell, J. H. Kahn, and T. G. Hornby, "Metabolic costs and muscle activity patterns during robotic- and therapist-assisted treadmill walking in individuals with incomplete spinal cord injury," Phys Ther, vol. 86, pp. 1466-78, 2006.