Published in final edited form as:

IEEE Trans Neural Syst Rehabil Eng. 2006 March ; 14(1): 55–63.

Adaptive Force Regulation of Muscle Strengthening Rehabilitation Device With Magnetorheological Fluids

Shufang Dong,

Department of Mechanical Engineering, University of Delaware, Newark, DE 19716 USA

Ke-Qian Lu,

Retired, Tianjin University, Tianjin 300072 China

Jian Qiao Sun, and

Department of Mechanical Engineering, University of Delaware, Newark, DE 19716 USA (e-mail: sun@me.udel.edu)

Katherine Rudolph

Department of Physical Therapy, University of Delaware, Newark, DE 19716 USA

Abstract

In rehabilitation from neuromuscular trauma or injury, strengthening exercises are often prescribed by physical therapists to recover as much function as possible. Strengthening equipment used in clinical settings range from low-cost devices, such as sandbag weights or elastic bands to large and expensive isotonic and isokinetic devices. The low-cost devices are incapable of measuring strength gains and apply resistance based on the lowest level of torque that is produced by a muscle group. Resistance that varies with joint angle can be achieved with isokinetic devices in which angular velocity is held constant and variable torque is generated when the patient attempts to move faster than the device but are ineffective if a patient cannot generate torque rapidly. In this paper, we report the development of a versatile rehabilitation device that can be used to strengthen different muscle groups based on the torque generating capability of the muscle that changes with joint angle. The device is low cost, is smaller than other commercially available machines, and can be programmed to apply resistance that is unique to a particular patient and that will optimize strengthening. The core of the device, a damper with smart magnetorheological fluids, provides passive exercise force. A digital adaptive control is capable of regulating exercise force precisely following the muscle strengthening profile prescribed by a physical therapist. The device could be programmed with artificial intelligence to dynamically adjust the target force profile to optimize rehabilitation effects. The device provides both isometric and isokinetic strength training and can be developed into a small, low-cost device that may be capable of providing optimal strengthening in the home.

Index Terms

Adaptive control; magnetorheological fluids; muscle strengthening; rehabilitation device

I. Introduction

Muscle strengthening is known to improve the recovery of normal joint functions after injuries [1]–[3]. To maximize rehabilitation effects, the strengthening protocol should adapt to variable muscle force corresponding to changing muscle fiber length and contraction velocity [4], [5]. Physical rehabilitation devices capable of delivering precisely controlled force are very limited on the market. Existing low-cost portable devices such as elastic bands, sandbags, and dumbbells provide constant force regardless of the range at which the joint is moving, thus, resistance is set to accommodate the muscle force production at the weaker ends of the range of motion.

Other sophisticated devices such as isokinetic dynamometers are expensive and large, and are designed only for clinical or hospital settings. Isokinetic dynamometers keep the speed of movement constant and force is generated when patients attempt to move faster than the prescribed speed. The patient must, however, be capable of meeting the speed of the lever arm in order to generate force that can produce a strengthening effect. This paper reports recent research results of an autonomous rehabilitation device capable of providing variable resistance regardless of the speed of movement that is smaller and less expensive than existing technology.

Muscle weakness can severely impact the functional status of patients following injury. Madsen *et al.* [6] found that quadriceps femoris strength was related to physical function. Quadriceps strength proved to be the strongest predictor of walking speed, stair climbing, speed and overall physical activity. The authors suggest that the main benefit of muscle strengthening may be to promote mobility. Others showed the importance of quadriceps strength in persons with knee osteoarthritis (OA) and fractured hips. Fisher *et al.* [2] studied the effect of three months of outpatient physical therapy treatments in which knee muscle strengthening was a focus in patients with OA. They found significant improvements in the ability to walk, rise from a chair, and climb stairs with increased quadriceps strength. Moxley–Scarborough *et al.* [7] found that quadriceps femoris muscle strength correlated with dynamic stability during rising from a chair and walking in functionally limited elderly individuals. The authors state that quadriceps femoris strength appears to enhance dynamic stability and may reduce the risk of falling in elderly individuals.

In recent years, there have been a growing number of investigations into the delivery of rehabilitation services in the home [8], [9], and through telemedicine [10]. Kane *et al.* [9] found differences in functional outcome based on the venue (nursing home, home with home-based health care, and rehabilitation centers) for posthospital care for patients with chronic obstructive pulmonary disease, congestive heart failure, hip procedures, and hip fractures. Patients were followed at six weeks, six months, and one year after discharge and the costs and benefits associated with the location that produced the greatest improvements were estimated. Patients who were discharged to nursing homes fared the worst and those sent to rehabilitation centers and home with home-based health care fared best. Patients who return home likely had higher levels of function and better general health prior to hospital admission than those going to nursing homes [11]. Rehabilitation centers typically provide more therapy services and have more equipment available to therapists who prescribe strengthening programs than nursing homes. Whether rehabilitation at home is a viable option depends on many factors including the quality and quantity of home-based rehabilitation. Providing more cost effective and versatile strength training equipment to therapists would improve the delivery of rehabilitation services in nursing homes, chronic care centers, and in the home.

Home-based rehabilitation offers benefits to patients who have difficulty making frequent visits to clinics to prevent decline in joint function [12]. It is desirable to develop functional rehabilitation devices that can be developed into devices appropriate for therapy in the home. The device studied in this paper makes use of magnetorheological fluids and adaptive control, and offers a user friendly, and programmable rehabilitation system for strengthening multiple muscle groups following a patient specific exercise protocol prescribed by a therapist. Although other commercial rehabilitation devices can be adapted for the home use, the programmable features of the current device make it unique.

Magnetorheological (MR) fluids are known as smart fluids that change the flow viscosity in milliseconds in response to the applied magnetic field. Dampers made of such smart fluids are widely used in vehicle suspension systems and civil structures to suppress vibrations. A MR damper typically has a compact mechanical design, and requires a low-voltage power supply [13]. The competing technologies include magnetitic particle dampers and friction dampers,

which often give less smooth mechanical response, involve more complicated mechanical designs, and require more power to actuate them. Like other dampers, the MR damper is highly nonlinear and demands extensive modeling and control effort [14]. In this study, we design an adaptive control for force tracking, which can tackle the nonlinearity and parameter uncertainties of the system. The adaptive control estimates the slowly time-varying uncertain parameters online, and maintains the stability of the closed-loop system [15]. The focus of the study is on the technical aspects of the proposed device, and not on its clinical effects. The clinical evaluation of the device is underway, and will be reported in the future.

This paper is organized as follows. Section II describes the rehabilitation device and the MR damper, and discusses the dynamic modeling and adaptive control of force tracking. Simulations and experimental results of adaptive force regulation are presented in Section III. Section IV discusses feasible clinical applications of the device. Section V concludes the paper.

II. Method

A. Description of Rehabilitation Device

A picture of the rehabilitation device in the form of a foldable chair is shown in Fig. 1. The frame of the chair is made of T-slot aluminum extrusion bars (80/20 Inc., Columbia City, IN). The mechanical layout of the device is illustrated in Fig. 2. The force arm will be strapped to a human limb in such a way that its rotation center matches the joint center. The force lever can be adjusted up and down, and rotated around a fixed point so that different joint systems can be exercised. The current prototype is suited for the knee and ankle joints. Strain gauges attached on the force arm measure the force in real time. An angular sensor on the rotation center records the joint position. The resistant force of the device is changed by altering the voltage across the excitation coil of the MR damper embedded inside the piston of the damper. We have developed a “dual piston” damper, as shown in Fig. 3 that can provide a force large enough to allow isometric evaluation of voluntary muscle contraction. The dual piston design also eliminates the need for volume compensation. The dimension of the chair is $1.2 \text{ m} \times 1.2 \text{ m} \times 1.5 \text{ m}$, and its weight is 45 kg. The total power consumption of the system is less than 100 W. The device is controlled via a laptop computer with LabView graphical interface. The range of motion is 135° . The maximum resistance torque at the force arm is 250 Nm, and the lower limit is 18 Nm. We have taken the peak torque profiles of five healthy young subjects for the quadriceps and hamstrings over a range of 20° – 70° of knee flexion at 10° intervals. The results are shown in Fig. 4. The largest torque 188 Nm is generated by the quadriceps muscles. Given the torques of the device, it is mechanically strong enough for exercise of a wide range of normal as well as pathological subjects.

B. Modeling of Exercise Force

In this application, the control is the voltage to the damper, and the output is the resistant force measured on the arm. The system is thus single input single output (SISO). *We treat the human reaction force and friction as disturbances.* We model the input-output relationship with adaptive infinite impulse response (IIR) filters. In the following, we compare a first order and a second order IIR filter to model the system. Experimental data of the system response subject to different excitations are collected for the modeling. The excitations include a step input and variable forcing. A least square algorithm is used to adapt the model parameters [16]. Because the device temperature does not change much, the friction force in the device is nearly constant during the operation.

Figs. 5-7 show the experimental results and the corresponding predictions from the first order and second order IIR model. Both models predict the system response reasonably well. The second order model does not offer obvious advantages over the first order one. For the

efficiency of the real time implementation, we choose the first order model to characterize the dynamics of the device.

C. Adaptive Force Regulation

System Model—The first-order IIR filter of the system is given by

$$y_{k+1} = ay_k + bu_k + d_k \quad (1)$$

where y_k denotes the force output, u_k is the control voltage, d_k is the disturbance, and k is the sample index. Since the plant is passive and dissipative, the open loop system is always stable so that $|a| < 1$. We also assume that $b_u > b > b_l > 0$ where b_l and b_u are the known lower and upper bounds of b , and that the disturbance and its increment over one sample interval are bounded

$$|d_k| \leq D, \delta d_k = |d_k - d_{k-1}| \leq \varepsilon. \quad (2)$$

Define a force tracking error as

$$e_k = y_k - y_{r,k} \quad (3)$$

where $y_{r,k}$ is the target force. The incremental dynamics of the system from (1) can be written as [17]

$$\delta e_{k+1} = a\delta y_k + b\delta u_k + \delta d_k - \delta y_{r,k+1} \quad (4)$$

where

$$\delta e_{k+1} = e_{k+1} - e_k$$

$$\delta y_k = y_k - y_{k-1}$$

$$\delta u_k = u_k - u_{k-1}$$

$$\delta y_{r,k+1} = y_{r,k+1} - y_{r,k}. \quad (5)$$

Nominal Control—When a and b are known exactly, and the control is unconstrained, we can design a nominal control to track the reference as

$$\delta u_k = -\frac{a}{b}\delta y_k - \frac{1}{b}[(1-\lambda)e_k - \delta y_{r,k+1}] \quad (6)$$

where $0 < \lambda < 1$. Substituting the nominal control into (4), we obtain the closed-loop system

$$e_{k+1} - \lambda e_k = \delta d_k. \quad (7)$$

Thus, the nominal closed-loop system is stable and the tracking error is bounded because $|\delta d_k| \leq \varepsilon$.

Adaptation Algorithm—When a and b are unknown, we consider an adaptive control as

$$\delta u_k = \theta_{1,k}w_{1,k} + \theta_{2,k}w_{2,k} \quad (8)$$

where $\theta_{1,k}$ and $\theta_{2,k}$ are two control gain parameters, $w_{1,k}$ and $w_{2,k}$ are two measurable signals defined as

$$w_{1,k} = \delta y_k, \quad w_{2,k} = (1 - \lambda)e_k - \delta y_{r,k+1}. \quad (9)$$

Since $w_{1,k}$ consists of only the state variable, and $w_{2,k}$ includes both the state variable and the reference, they are linearly independent. Substituting (8) into (4), we have

$$e_{k+1} - \lambda e_k = [b\theta_{1,k} + a]w_{1,k} + [b\theta_{2,k} + 1]w_{2,k} + \delta d_k. \quad (10)$$

Note that when $b\theta_{1,k} + a = 0$ and $b\theta_{2,k} + 1 = 0$, we recover the nominal system. Let $\theta_1^* = -(a/b)$ and $\theta_2^* = -(1/b)$. θ_1^* and θ_2^* are the desired values of $\theta_{1,k}$ and $\theta_{2,k}$. Define the parameter estimation errors as $\tilde{\theta}_{1,k} = \theta_{1,k} - \theta_1^*$ and $\tilde{\theta}_{2,k} = \theta_{2,k} - \theta_2^*$. Equation (10) reads

$$e_{k+1} - \lambda e_k = b(\tilde{\theta}_{1,k}w_{1,k} + \tilde{\theta}_{2,k}w_{2,k}) + \delta d_k. \quad (11)$$

Equation (11) contains the parameter estimation errors $\tilde{\theta}_{1,k}$ and $\tilde{\theta}_{2,k}$ referenced to the corresponding exact values. To derive an adaptation rule for $\theta_{1,k}$ and $\theta_{2,k}$ based on their previous values, we consider an extended parameter estimation error E_{k+1} as [18]

$$E_{k+1} = e_{k+1} - b_{k+1}(\theta_{1,k} - \theta_{1,k+1})w_{1,k} - \lambda e_k - b_{k+1}(\theta_{2,k} - \theta_{2,k+1})w_{2,k} \quad (12)$$

where b_k is the online estimation of b . Let $\tilde{b}_k = b_k - b$. Substituting (11) into (12), we obtain an equation governing the evolution of the extended error

$$E_{k+1} = b(\tilde{\theta}_{1,k+1}w_{1,k} + \tilde{\theta}_{2,k+1}w_{2,k}) + \tilde{b}_{k+1}\xi_k + \delta d_k \quad (13)$$

where

$$\xi_k = (\theta_{1,k+1} - \theta_{1,k})w_{1,k} + (\theta_{2,k+1} - \theta_{2,k})w_{2,k}. \quad (14)$$

It is now clear that when the disturbance does not exist $\delta d_k = 0$, E_{k+1} is dictated by the parameter estimation errors $\tilde{\theta}_{1,k}$ and $\tilde{\theta}_{2,k}$ and the incremental changes of the parameter estimations and $\theta_{1,k+1} - \theta_{1,k}$ and $\theta_{2,k+1} - \theta_{2,k}$. Therefore, it is a measure of the parameter estimation.

We then apply the gradient search algorithm with dead-zone [19] to adapt the parameters $\theta_{1,k}$, $\theta_{2,k}$, and b_k so that

$$\begin{aligned} \theta_{1,k+1} &= \theta_{1,k} - \frac{\Gamma_1 E_k}{m_k^2} w_{1,k-1} \\ \theta_{2,k+1} &= \theta_{2,k} - \frac{\Gamma_2 E_k}{m_k^2} w_{2,k-1} \\ b_{k+1} &= b_k - \frac{\eta E_k}{m_k^2} \xi_{k-1} \end{aligned} \quad (15)$$

where

$$m_k^2 = 1 + w_{1,k-1}^2 + w_{2,k-1}^2 + \xi_{k-1}^2. \quad (16)$$

The adaptation gains are selected such that

$$\Gamma_1 = \Gamma_2 = \eta = 0, |E_k| \leq \gamma\epsilon \quad (17)$$

and

$$\begin{aligned} 0 < \Gamma_1 &< \frac{2}{b_y}(1 - \gamma^{-1}) \\ 0 < \Gamma_2 &< \frac{2}{b_u}(1 - \gamma^{-1}), |E_k| > \gamma\epsilon \\ 0 < \eta &< 2(1 - \gamma^{-1}) \end{aligned} \quad (18)$$

where $1 < \gamma < \infty$ defines the width of the boundary layer in terms of ϵ . When E_k is sufficiently small in magnitude, it is common to turn off the adaptation of parameters since the control performance is usually good at this point and further adaptations with large gains will cause oscillations or chattering in parameter estimations. $|E_k| \leq \gamma\epsilon \ll 1$ defines a “boundary layer” around the zero $E_k = 0$. The choice of the boundary layer width γ in terms of the parameter ϵ is usually empirical.

Stability Analysis—We have designed the adaptive control in (8) and the parameter adaptation algorithm in (15). We now need to show that the closed loop system is stable. To prove stability, we resort to the Lyapunov stability theory [15]. The proof presented here follows the lines in [17] and [18].

Consider a Lyapunov function

$$V_k(\tilde{\theta}_1, \tilde{\theta}_2, \tilde{b}) = b \left(\frac{\tilde{\theta}_{1,k}^2}{\Gamma_1} + \frac{\tilde{\theta}_{2,k}^2}{\Gamma_2} \right) + \frac{\tilde{b}_k^2}{\eta}. \quad (19)$$

When $|E_k| \leq \gamma\epsilon$, the adaptation stops so that $V_{k+1} = V_k$, $\theta_{1,k} = \theta_{1,k+1}$ and $\theta_{2,k} = \theta_{2,k+1}$. From (12), we have

$$|e_{k+1}| \leq \lambda |e_k| + \gamma\epsilon. \quad (20)$$

Since $0 < \lambda < 1$, $|e_k|$ is bounded. As $k \rightarrow \infty$, $|e_k| \rightarrow e_\infty$. We have

$$e_\infty \leq \frac{\gamma}{1 - \lambda} \epsilon. \quad (21)$$

Note that the boundedness of $|e_k|$ implies the same of $|y_k|$. Hence, the system is stable in the boundary layer.

When $|E_k| > \gamma\epsilon$, we have $|\delta d_{k-1}| \leq \epsilon < (|E_k|/\gamma)$, and

$$\begin{aligned} V_{k+1} - V_k &= \frac{bE_k^2(\Gamma_1 w_{1,k-1}^2 + \Gamma_2 w_{2,k-1}^2)}{m_k^4} + \frac{\eta E_k^2 \epsilon_{k-1}^2}{m_k^4} - 2(E_k - \delta d_{k-1}) \frac{E_k}{m_k^2} \\ &< \left[\frac{b(\Gamma_1 w_{1,k-1}^2 + \Gamma_2 w_{2,k-1}^2) + \eta \epsilon_{k-1}^2}{m_k^2} - 2(1 - \gamma^{-1}) \right] \frac{E_k^2}{m_k^2} \\ &\leq 0. \end{aligned} \quad (22)$$

Hence, $V_{k+1} - V_k$ is negative-semidefinite, and the parameter estimation error is upper bounded.

Proof of Bounded Signals—We have shown that both $|e_k|$ and $|y_k|$ are bounded when $|E_k| \leq \gamma\epsilon$, and that when $|E_k| > \gamma\epsilon$, the system is stable in the Lyapunov sense: $V_k > 0$ and

$V_{k+1} - V_k \leq 0$. Since V_k only contains parameter estimation errors, we must show that when $|E_k| > \gamma\epsilon$, $|e_k|$ and $|y_k|$ are still bounded.

Equation (22) suggests that $|\theta_{1,k+1} - \theta_{1,k}| \rightarrow 0$, $|\theta_{2,k+1} - \theta_{2,k}| \rightarrow 0$, $|b_{k+1} - b_k| \rightarrow 0$, and $|(E_k/m_k)| \rightarrow 0$ as $k \rightarrow \infty$. From the definitions of $w_{1,k}$, $w_{2,k}$, ξ_k and m_k , we have

$$\begin{aligned} |w_{1,k-1}| &\leq |y_{k-1}| + |y_{k-2}| \\ |w_{2,k-1}| &\leq (1-\lambda)|y_{k-1}| + \beta_r \\ |\xi_{k-1}| &\leq \beta_1|y_{k-1}| + \beta_2|y_{k-2}| + \beta_3 \\ w_{2,k}m_k &\leq 1 + |w_{1,k-1}| + |w_{2,k-1}| + |\xi_{k-1}| \\ w_{1,k-1} &\leq \alpha_1|y_{k-1}| + \alpha_2|y_{k-2}| + \alpha_3 \end{aligned} \quad (23)$$

where β_r is a positive constant such that $(1-\lambda)|y_{r,k-1}| + |\delta y_{r,k}| \leq \beta_r$. $\beta_1, \beta_2, \beta_3, \alpha_1, \alpha_2$ and α_3 are positive constants. Applying these inequalities into (12), we have

$$\begin{aligned} |e_k| &\leq \frac{E_k}{m_k} |(\alpha_1|y_{k-1}| + \alpha_2|y_{k-2}| + \alpha_3) \\ &\quad + |\theta_{1,k-1} - \theta_{1,k}| |b_k| (|y_{k-1}| + |y_{k-2}|) \\ &\quad + |\theta_{2,k-1} - \theta_{2,k}| |b_k| [(1-\lambda)|y_{k-1}| + \beta_r] \\ &\quad + \lambda |e_{k-1}|. \end{aligned} \quad (24)$$

Since $|e_k| = |y_k - y_{r,k}|$, the above equation reads

$$\begin{aligned} |y_k| &\leq \lambda |y_{k-1}| + |y_{r,k}| + \lambda |y_{r,k-1}| \\ &\quad + \frac{E_k}{m_k} |(\alpha_1|y_{k-1}| + \alpha_2|y_{k-2}| + \alpha_3) \\ &\quad + |\theta_{1,k-1} - \theta_{1,k}| |b_k| (|y_{k-1}| + |y_{k-2}|) \\ &\quad + |\theta_{2,k-1} - \theta_{2,k}| |b_k| [(1-\lambda)|y_{k-1}| + \beta_r]. \end{aligned} \quad (25)$$

Since $\lim_{k \rightarrow \infty} |\theta_{1,k+1} - \theta_{1,k}| = 0$, $\lim_{k \rightarrow \infty} |\theta_{2,k+1} - \theta_{2,k}| = 0$, $\lim_{k \rightarrow \infty} |(E_k/m_k)| = 0$, (25) implies the boundedness of y_k . The bounded y_k also implies the boundedness of e_k and m_k . Hence, we have $\lim_{k \rightarrow \infty} |E_k| = 0$. This contradicts the assumption that $|E_k| > \gamma\epsilon$ as $k \rightarrow \infty$. Therefore, we must always have $0 < \lim_{k \rightarrow \infty} |E_k| \leq \gamma\epsilon$.

This suggests that $|E_k|$ will decrease from its initial value until $|E_k| \leq \gamma\epsilon$. From this point on, the system is stable and the tracking error is bounded as indicated in (21). Equation (22) suggests that the boundary layer as defined by $|E_k| \leq \gamma\epsilon$ is attractive.

III. RESULTS

To demonstrate the effectiveness of the proposed modeling and control algorithms, we present numerical simulations and experimental results of the control system. In the numerical simulations, we first assume that the disturbance is constant. We examine the convergence of the parameter estimation and force tracking performance. Then, we study variable disturbances to investigate the robustness of the control.

In the experimental validation of the control algorithm, we consider a step force tracking with slow and fast knee flexions, a sinusoidal force tracking with slow and fast knee flexions. A good tracking performance in these exercises implies a broad adaptability of the control system.

A. Simulation Results

We first consider the system subject to a constant disturbance given by $y_{k+1} = 0.96y_k + 1.2u_k + 1$. The desired values of the parameter estimation are $\theta_1^* = -0.8$, $\theta_2^* = -0.83$, and $b = 1.2$. The initial values of the parameter estimation are chosen to be $\theta_{1,0} = -1$, $\theta_{2,0} = -0.9$, and $b_0 = 1.1$.

The initial value of the control is set to zero. The oscillatory target force is $y_{r,k} = 80 + 15 \sin(k/3) + 25 \cos(k/5) + 10 \sin(k/7)$. The adaptation gains are $\Gamma_1 = \Gamma_2 = \eta = 0.3$, the gain λ is set to 0.7. Simulation results are shown in Fig. 8. In the simulation, we do not impose limits on the control. The tracking performance is very good, and the estimated parameters converge to their true values.

Simulation results of the system with a variable disturbance $y_{k+1} = 0.96y_k + 1.2u_k + 1 + \sin(k)$ are shown in Fig. 9. We have chosen the adaptation boundary layer parameter $\varepsilon = 0.9$, $\gamma = 1.1$, and adaptation gains $\Gamma_1 = \Gamma_2 = \eta = 0.1$. Other conditions are the same as before. The tracking performance exhibits strong robustness to the variable disturbance and unknown plant parameters. The control is smooth, and the estimated parameters are bounded and gradually converge to their true values.

Note that the parameters used in the simulations describe the plant dynamics and adaptation gains and do not have physiological meanings.

B. Experimental Results

Four sets of experimental data are collected and presented in Figs. 10-13. The figures show the force tracking, the control, and the estimated parameters θ_1 and θ_2 . The sample frequency is 200 Hz. The control is limited to the range 0–8 V. When the control is saturated, the parameter adaptation is suspended. In the experiments, we also have $\gamma = 2$, $\varepsilon = 0.5$, $\Gamma_1 = \Gamma_2 = \eta = 0.03$ and $\lambda = 0.7$. The range of the joint motion is from 15° to 90°.

One healthy male adult (height 174 cm, weight 82 kg, age 60 years old) was the subject of the experiments. The subject was instructed to flex and extend the knee joint with the full effort against the resistance without looking at the computer monitor. Each session consisted of twenty cycles. Before each session, the subject was asked to exercise with different joint speeds. The experiment was done over several days. In the end, we tested the device at four different average knee flexion speeds: 35°/s, 58°/s, 220°/s, and 234°/s. In general, all the experiments show good force tracking performance. We note that the fast motion tends to produce larger fluctuating disturbances than the slow motion does.

The objective of the experimental study is to validate the performance of the device as well as the control algorithm. For this reason, we did not test the device on a large number of subjects.

C. A Note on Sensitivity

The effect of the amplitude of disturbances is clear from (7). It essentially affects the steady state tracking accuracy. Assume that in the steady state, the parameter estimation converges, we then have $k \rightarrow \infty$, $\tilde{\theta}_{1,k} \rightarrow 0$ and $\tilde{\theta}_{2,k} \rightarrow 0$. Hence, we have

$$e_\infty = \frac{\delta d_\infty}{1 - \lambda}. \quad (26)$$

The control gain λ affects the stability of the nominal control system (7). It must be $0 < \lambda < 1$.

Once the system model and control structure are chosen, the performance of the control system is largely the function of three adaptation gains Γ_1 , Γ_2 , and η . Since the gradient search is used in the adaptation, the influence of adaptation gains on the estimation and control is well studied [20]. Within the limits given in (18), the larger gains may lead to larger changes in the parameter estimations for each step, as shown in (15). Since the boundary layer strategy is implemented here, the chattering in adaptation is eliminated. From (22), we have the minimum change of V_k over one step, when Γ_1 , Γ_2 , and η take their maximum values

$$\min (V_{k+1} - V_k) = -\frac{2(1 - \gamma^{-1})E_k^2}{m_k^4} \quad (27)$$

and the maximum change of V_k , when $\Gamma_1 = \Gamma_2 = \eta = 0$

$$\max (V_{k+1} - V_k) = -\frac{2(1 - \gamma^{-1})E_k^2}{m_k^2}. \quad (28)$$

Hence, when larger gains are used, the convergence of the adaptation can slow down by at most a factor of m_k^{-2} . Note that $m_k^2 > 1$ as defined in (16).

IV. DISCUSSION

Based on the fact that the device can accurately track the force prescribed by the physical therapist for a patient, and can take isometric measurements of patients, we discuss some feasible rehabilitation applications of the device. Muscles produce force according to a length-tension relationship in which the highest force is generated at an optimal muscle fiber length and less force is generated at longer and shorter muscle lengths [21], [22]. Muscle torque is also influenced by the changes in moment arm length that occur when a joint moves through a range of motion [23], [24], as well as the speed of contraction [25]. During concentric contractions when the muscle shortens, as contraction speed increases, torque output decreases. Therefore, muscles such as the quadriceps femoris group produce greater torque in the middle of the range of knee motion (approximately 60° of knee flexion) and at slower speeds. This serves as the basis for the prescribed rehabilitation with this device that is capable of providing resistance that changes based on physiologic properties of muscle as well as unique characteristics of individual patients.

The physical therapist can determine the maximum torque output of a muscle group at different joint positions to generate a torque profile. This torque profile can then be used to prescribe customized exercise protocols based on the judgement of the therapist that can be designed to vary based on the conditions of the patient.

For example, some patients develop profound quadriceps femoris weakness after surgical procedures such as an anterior cruciate ligament reconstruction or total knee arthroplasty [26]. Quadriceps weakness is often accompanied by what is referred to as a “quad-lag” i.e., patients can produce enough torque in the middle of the range of motion to extend the knee actively, but when they attempt to extend the knee to the end of the extension range, they are incapable of doing so or they require slower movement velocity to achieve adequate torque.

In such cases, therapy would generally begin with isometric contractions in the fully extended position and progress to isotonic or isokinetic training through the full joint motion. In order to strengthen the quadriceps through the full range of motion, isotonic resistance from sandbag weights or elastic bands would require that the patient use very low resistance so they could achieve full knee extension. If isokinetic devices were used, slow speeds would be required. A separate set of exercises might be prescribed in which higher resistance or faster speed was used to strengthen the muscle in its stronger ranges and faster speeds.

With the device described in this paper, patients could exercise against higher resistance in the stronger range of motion and lower resistance in the weaker range at whatever speed they are capable of producing. This would reduce the total number of exercise repetitions to achieve a strengthening effect across the full range since the resistance can be optimized.

One limitation of the current prototype is the off-state force that is generated due to fluid mechanics. The lower limit of the device, approximately 18 Nm, would prove too high for some patient populations including the clinical example described above. When low resistances are needed, the lower limit can be minimized by using slow movement speeds. In future development, a small motor could be incorporated into the design to overcome the off-state resistance of the MR fluid damper. Nevertheless, at present, MR fluids are still the best choice to make variable resistance devices for rehabilitation that require low voltage, deliver large forces and torques, and can be made compact and light weight by professional engineers.

Another interesting feature of the device is that it can be incorporated with artificial intelligence to adapt to the exercise response. For example, if a patient was experiencing muscle fatigue, they may find it more difficult to meet the prescribed torque goal or may do so over increasingly longer time periods. On the other hand, as strengthening occurs, patients may achieve the prescribed torque goal quite quickly or they may consistently exceed the goals. The device could be programmed to increase or decrease the targeted goal automatically thereby optimizing strengthening and possibly reducing injury. This may be particularly important in patient populations such as individuals with fibromyalgia or multiple sclerosis whose symptoms may increase from excessive exercise intensity.

An example is shown in Figs. 14 and 15. Fig. 14 indicates that the patient can initially keep up with the prescribed force profile very well. Fig. 15 shows the exercise cycle time and the corresponding percentage change of the initial force setting by considering the fatigue of the muscle. The force profile is lowered by a small percentage when the cycle time exceeds a preset level to maintain a constant speed during the exercise, assuming that this is desired by the physical therapist. The current device provides an effective means to quickly detect changes in muscle function and adjust itself appropriately. We are currently investigating these types of treatment progression algorithms.

Our future work will investigate the design of a smaller device that could be transported to a patient's home, determine the needs of the patient, measure the isometric force profile, and program the device with the rehabilitation protocol. The patient could then follow the protocol at home and the device could record the exercise progress over many exercise sessions. The therapist could make periodic visits to assess the patient's condition and to modify the exercise prescription.

Other optimal exercise protocols for specific medical conditions can also be implemented with the help of the device. These will be the topics of our future research.

V. CONCLUSION

We developed a muscle strengthening rehabilitation device that provides a unique type of resistance that can be programmed specifically for each patient. The adaptive tracking algorithm makes the device capable of providing variable and optimal strengthening forces for exercise. The simulation and experimental results have demonstrated the validity of the algorithm. The automatic adjusting mechanism of the exercise force profile with the help of artificial intelligence offers flexibility for diverse rehabilitation needs. The device is currently under clinical evaluations. Furthermore, the adaptive modeling and control studies presented in this paper may also be applied to automate other commercial rehabilitation devices.

Acknowledgements

This work is supported by the National Institutes of Health under Grant 5 R21 HD040956-03.

References

1. Ide J, Maeda S, Yamaga M, Morisawa K, Takagi K. Shoulder-strengthening exercise with an orthosis for multidirectional shoulder instability: Quantitative evaluation of rotational shoulder strength before and after the exercise program. *J Shoulder Elbow Surg* 2003;12(4):342–345. [PubMed: 12934027]
2. Fisher NM, Gresham GE, Abrams M, Hicks J, Horrigan D, Pendergast DR. Quantitative effects of physical therapy on muscular and functional performance in subjects with osteoarthritis of the knees. *Arch Phys Med Rehabil* 1993;74(8):840–847. [PubMed: 8347069]
3. Dodd KJ, Taylor NF, Damiano DL. A systematic review of the effectiveness of strength-training programs for people with cerebral palsy. *Arch Phys Med Rehabil* 2002;83(8):1157–1164. [PubMed: 12161840]
4. Hill AV. The heat of shortening and the dynamic constants of muscle. *Proc R Soc London Series B* 1938;126:136–195.
5. Gordon AM, Huxley AF, Julian FJ. The variation in isometric tension with sarcomere length in vertebrate muscle fibers. *J Physiology* 1966;184:170–192.
6. Madsen OR, Lauridsen UB, Sorensen OH. Quadriceps strength in women with a previous hip fracture: Relationships to physical ability and bone mass. *Scand J Rehabil Med* 2000;32(1):37–40. [PubMed: 10782940]
7. Scarborough DM, Krebs DE, Harris BA. Quadriceps muscle strength and dynamic stability in elderly persons. *Gait Posture* 1999;10(1):10–20. [PubMed: 10469937]
8. Penrod JD, Kane RL, Finch MD, Kane RA. Effects of posthospital medicare home health and informal care on patient functional status. *Health Services Res* 1998;33(3):513–529.pt. 1
9. Kane RL, Chen Q, Finch M, Blewett L, Burns R, Moskowitz M. The optimal outcomes of post-hospital care under medicare. *Health Services Res* 2000;35(3):615–661.
10. Burdea G, Popescu V, Hentz V, Colbert K. Virtual reality-based orthopedic telerehabilitation. *IEEE Trans Rehabil Eng Sep*;2000 8(3):430–432. [PubMed: 11001524]
11. Thorngren KG, Ceder L, Svensson K. Predicting results of rehabilitation after hip fracture. A ten-year follow-up study. *Clin Orthop Related Res* 1993;287:76–81.
12. Gill TM, Baker DI, Gottschalk M, Peduzzi PN, Allore H, Van Ness PH. A prehabilitation program for the prevention of functional decline: Effect on higher-level physical function. *Arch Phys Med Rehabil* 2004;85(7):1043–1049. [PubMed: 15241748]
13. Spencer BF Jr, Dyke SJ, Sain MK, Carlson JD. Phenomenological model for magnetorheological dampers. *J Eng Mech* 1997;123(3):230–238.
14. Sims ND, Holmes NJ, Stanway R. A unified modeling and model updating procedure for electrorheological and magnetorheological vibration dampers. *Smart Mater Structures* 2004;13(1):100–121.
15. Slotine, JJE.; Li, W. *Applied Nonlinear Control*. Englewood Cliffs, NJ: Prentice-Hall; 1991.
16. Ljung, L. *System Identification—Theory for the User*. Englewood Cliffs, NJ: Prentice-Hall; 1987.
17. Chan CY. Discrete adaptive sliding-mode tracking controller. *Automatica* 1997;33(5):999–1002.
18. Tao, G. *Adaptive Control Design and Analysis*. Hoboken, NJ: Wiley; 2003.
19. Goodwin, GC.; Sin, KS. *Adaptive Filtering, Prediction and Control*. Englewood Cliffs, NJ: Prentice-Hall; 1984.
20. Widrow, B.; Stearns, SD. *Adaptive Signal Processing*. Englewood Cliffs, NJ: Prentice-Hall; 1985.
21. Gordon AM, Huxley AF, Julian FJ. The variation in isometric tension with sarcomere length in vertebrate muscle fibers. *J Physiol (London)* 1966;184(1):170–192. [PubMed: 5921536]
22. Currier DP. Evaluation of the use of a wedge in quadriceps strengthening. *Physical Therapy* 1975;55(8):870–874. [PubMed: 1144526]
23. Smidt GL. Biomechanical analysis of knee flexion and extension. *J Biomech* 1973;6(1):79–92. [PubMed: 4693870]
24. Visser JJ, Hoogkamer JE, Bobbert MF, Huijing PA. Length and moment arm of human leg muscles as a function of knee and hip-joint angles. *Eur J Appl Physiol* 1990;61(5–6):453–60.
25. Thorstensson A, Grimby G, Karlsson J. Force-velocity relations and fiber composition in human knee extensor muscles. *J Appl Physiol* 1976;40(1):12–6. [PubMed: 1248977]

26. Barrack RL, Stanley T, Butler RA. Treating extensor mechanism disruption after total knee arthroplasty. Clin Orthop Related Res 2003;(416):98–104.

Biography

Shufang Dong received the B.S. degree from Beijing Institute of Technology, Beijing, China, in 1994 and the M.S. degree in mechanical engineering from Shanghai Jiaotong University, Shanghai, China, in 1997. He is currently working toward the Ph.D. in the Department of Mechanical Engineering, University of Delaware, Newark, with research interests in physical rehabilitation devices, biomechanics of human movement, smart fluids, and applied nonlinear control.

He was with the United Automotive Electronics System Company, Shanghai, China, as an Injection Molding Engineer, and Product and Equipment Engineer, specializing in automatic engine management systems until 2001.

Ke-Qian Lu received the M.S. degree in electrical engineering from Tianjin University, Tianjin, China, in 1964.

He was a Professor of Measurement and Electronic Engineering at Tianjin University before retirement. He was a Researcher in the Department of Mechanical Engineering at University of Delaware, Newark, from 2001 to 2004.

Jian Qiao Sun received the Ph.D. degree from University of California, Berkeley, in 1988.

He was with the Lord Corporation at their Corporate Research and Development Center, Cary, NC, and since engaged in smart materials research and applications, and acoustic-structural controls. In 1994, he joined the Faculty of the Department of Mechanical Engineering, University of Delaware, Newark, as an Assistant Professor, and was promoted to Associate Professor in 1998 and to Professor in 2003. He was an Associated Editor of American Society of Mechanical Engineers *Journal of Vibration and Acoustics* from 1994 to 2000, and has been

an Associated Editor of *Communications in Nonlinear Science and Numerical Simulations* since 2001 and an Editorial Member of *Acta Mechanica Solida Sinica* since 2003. His research interests include nonlinear random vibrations, nonlinear controls, active structural-acoustic control, modeling, and application of smart materials.

Katherine Rudolph received the M.S. degree in physical therapy from Boston University, Boston, MA, in 1989 and the Ph.D. degree in biomechanics and movement sciences from the University of Delaware, Newark, in 1998.

She joined the Faculty of the Department of Physical Therapy and Program in Biomechanics and Movement Sciences, University of Delaware, in 1999 and is currently an Assistant Professor. She has served as a manuscript reviewer for the *Journal of Orthopaedic and Sports Physical Therapy*, *Archives of Physical Medicine and Rehabilitation*, *Journal of Applied Biomechanics*, and the *European Journal of Applied Physiology*, and has reviewed grants for the National Institutes of Health Musculoskeletal and Rehabilitation Sciences Study section. Her research interests include analysis of walking in patients with knee osteoarthritis and neurological injury and development of research based physical therapy interventions.

Fig. 1.
Front view of muscle strengthening rehabilitation device when the knee joint is exercised.

Fig. 2.
Schematic of the rehabilitation device.

Fig. 3.
Design schematic of the MR damper.

Fig. 4.

Peak torque profiles of five healthy young subjects for the quadriceps and hamstrings over a range of 20°–70° of knee flexion at 10° intervals. Largest torque 188 Nm is generated by the quadriceps muscles.

Fig. 5.

System identification and validation of the IIR model. Case 1: The step torque response. Solid line: Experimental data. Dashed line: Adaptive estimations.

Fig. 6.

System identification and validation of the IIR model. Case 2: Variable torque tracking with fast motion. Solid line: Experimental data. Dashed line: Adaptive estimations.

Fig. 7.

System identification and validation of the IIR model. Case 3: Variable torque tracking with slow motion. Solid line: Experimental data. Dashed line: Adaptive estimations.

Fig. 8.

Simulation results of the torque tracking control and parameter estimations in the presence of a constant disturbance. Solid line: Torque reference or the true value. Dashed line: Actual torque or estimations.

Fig. 9.

Simulation results of the torque tracking control and parameter estimations in the presence of variable disturbances. Solid line: Torque reference or the true value. Dashed line: Actual torque or estimations.

Fig. 10. Experimental results of the step torque tracking with fast knee flexion. Solid line: Torque reference. Dashed line: Actual torque.

Fig. 11.

Experimental results of the step torque tracking with slow knee flexion. Solid line: Torque reference. Dashed line: Actual torque.

Fig. 12.

Experimental results of the variable torque tracking with fast knee flexion. Solid line: Torque reference. Dashed line: Actual torque.

Fig. 13.

Experimental results of the variable torque tracking with slow knee flexion. Solid line: Torque reference. Dashed line: Actual torque.

Fig. 14.

Knee flexion exercise following a target torque profile at 70% of the isokinetic level of the patient. Solid line: Target torque profile. Dashed line: Actual exercise torque.

Fig. 15.

Muscle fatigue and automatic compensation of the target torque profile as a percentage of the initial setting. Top: Solid line: Set time threshold. Dotted line with cycle: Actual exercise cycle time.