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Slacking by the Human Motor System: Computational Models and Implications for Robotic Orthoses

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***Abstract*— Recent experimental evidence suggests that a fundamental property of the human motor system is that it "slacks"; that is, that it continuously attempts to decrease levels of muscle activation when movement error is small during repetitive motions. This paper reviews several computational models of slacking, and discusses implications of slacking for the design of robotic orthoses. For therapeutic applications of robotic orthoses, slacking may reduce human effort during rehabilitation training, with negative consequences for use-dependent motor recovery. For assistive applications of robotic orthoses, slacking may allow the motor system to learn to take advantage of force amplification provided by an orthosis, with positive consequences for human energy efficiency.**

I. Introduction

There is increasing interest in developing robotic orthoses that physically assist people in walking or in performing upper extremity movements [1, 2]. Applications of this technology include rehabilitation therapy for people who are recovering from neurologic injuries [2], and assistive devices that allow people with or without disabilities to perform daily tasks, such as walking, more effectively [1].

For both of these applications an important consideration is the way in which the assistance provided by the robotic orthosis modulates the force production of the user. For therapeutic applications, high levels of patient effort are thought to be important for building muscle strength and for facilitating motor learning [3]. Improvements in cardiopulmonary conditioning also depend on the level of energy expended during training. Therefore it seems desirable that the assistance provided by a therapeutic orthosis be provided in such a way so that the orthosis does not "take over" and eliminate force production by the user.

On the other hand, for assistive applications, the goal is often to reduce the energy output of the user, so the user can walk longer with heavier loads, for example [1]. In this case, it would be desirable for the orthosis to take over force production while leaving movement control to the user.

Achieving these design goals requires understanding how the human motor system adapts to externally applied force. Recent evidence suggests that a fundamental property of the human motor system is that it continuously attempts to decrease levels of muscle activation during repeated movement when movement errors are small [4-6]. This paper describes several computational models of slacking, then shows how these models can be used to predict and optimize human responses to robotic orthoses.

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II. Computational Models of Human Slacking

A. Discrete model of slacking based on changes in limb force production

Consider a repetitive movement such as walking on a flat surface or reaching repeatedly to a fixed target. Assume that each movement produces an error that can be summarized with a scalar variable e. Here, we assume movement error is kinematic, but it could also be a force error or an error related to balance or gait speed. To reduce kinematic movement error, the human motor system generates feedforward commands for the relevant muscles using an internal model of the limbs and the task dynamics [7]. Recent experiments in which the task dynamics were suddenly altered indicate that the feedforward muscle force u_{i+1} for the next movement (i.e. the i^{th} + 1 movement) is generated by adjusting the last-used feedforward muscle force u_i (i.e. that for the i^{th} movement) based on the movement error e_i on the i^{th} movement [5, 8]. The general modeling paradigm is:

$$u_{i+1} = F(u_i) - G(e_i) \qquad (1)$$

where u_i is a scalar parameter that summarizes, for example, the maximum or mean force applied on movement i, or a scaling factor for a force waveform. F is a function that represents a neural process of recall from some sort of storage of the previously-tried command u_i, and G is a function that implements error-based learning. Several recent studies [5, 8, 9] have shown that linear versions of F and G can account for 80-90% of the variance of movement error during adaptation to novel dynamic environments for reaching or walking movements, resulting in an equation of this form:

$$u_{i+1} = fu_i - ge_i \qquad (2)$$

where f and g are constants.

The constant "f" has sometimes been termed a forgetting factor (e.g. [5]), which implies an unintentional loss of fidelity in recall from neural storage. In this paper, we will call the constant f the "slacking factor" because we contend it implements a planned mechanism for minimizing effort, rather than an unintentional error in recall. As support, Emken et al. [5] showed that the update law of Equation 2 implements a greedy minimization of the sum of error and effort, with the constant f determining the weighting of effort in the cost function. For reference, Emken et al. [5] found that f is about 0.6 – 0.8 when adapting to a viscous force field applied to the ankle during walking.

Equation 2 defines the slacking process: when movement error e_i is small, then the motor command u_i will decay exponentially from movement to movement with a time constant $\tau = -1/\ln(f)$, if $0 < f < 1$. Thus, Equation 2 indicates that the motor system continuously attempts to decrease levels of muscle activation during a repeated movement when movement errors are small.

Slacking can be difficult to detect because it typically increases movement errors as it progresses, triggering error-corrective motor processes that raise muscle activation, resulting in no net decrease in muscle activation. An experimental protocol was developed by Scheidt et al. [4] that circumvented this problem. This protocol has recently been named an "error clamp" [10]. In this protocol, applied first to straight-line reaching movements in robotic force fields, a person was allowed to adapt to a novel environment, which required that the person adjust the motor command u to some non-nominal value. Then the environment was reverted to a virtual, straight-line channel, which had the effect of "clamping" kinematic error during reaching to be zero, no matter what motor command the subject used. Scheidt et al. [4] found that the motor command that generated force against the channel decayed exponentially toward zero over many movements in this condition (mean time constant across 6 healthy subjects τ = 138 trials), consistent with slacking in Equation 2 with e = 0.

B. *Slacking in terms of changes in muscle activation*

A shortcoming of the formulation in Equation 2 is that it cannot explain the activation patterns of individual muscles, or the phenomenon of impedance control. Franklin et al. [11] recently proposed an elegant model that addresses these shortcomings. In this model, the motor system adjusts the activations of individual muscles in response to movement errors using the following update law:

$$u_{i+1} = u_i - G(e_i) \quad (3)$$

where $u_i > 0$ now represents the amount of feedforward muscle activation and e_i the muscle length error. The update function G is the sunken, asymmetric "V" shown in Figure 1. Since the update function is a "V", the motor system increases muscle activation of both agonist and antagonist when muscle length error is either positive or negative, resulting in co-contraction. Because the V is asymmetric, the activation of the muscle that was lengthened increases more, contributing to the development of a feedforward term to cancel the error. Franklin et al [11] showed how changes in muscle activation recorded for movements in a variety of novel dynamic environments fall along this V. This simple update rule also accurately predicts directionally-dependent changes in limb impedance in unstable force fields.

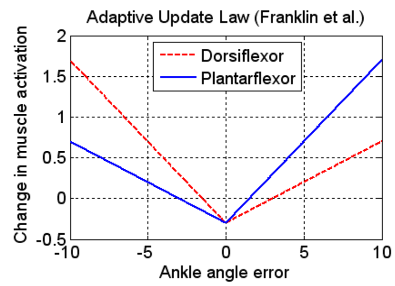

Figure 1. Muscle activation update law proposed by Franklin et al. [11]. Shown are update rules for two opposing muscles. Units are arbitrary.

Because the point of the "V" function is sunken below the x-axis, this update law reduces muscle activation when muscle error is zero – i.e. it predicts slacking. The form of slacking predicted is a linear rather than exponential decrease in activation, since muscle activation is reduced by a constant (defined by how sunken the V is) for each movement when error is small.

The force decay data from the Scheidt et al. error clamp experiment appeared to be exponential (see Figure 5 in [4]). A possible way to account for an exponential decay in the Franklin framework is the following update law:

$$u_{i+1} = fu_i - G_1(e_i) \quad (4)$$

where $0 < f < 1$ is a forgetting factor, and the error function G_1 is now a non-sunken, asymmetric V. Equation 4 predicts an exponential decrease in muscle activation when muscle length error is zero. The change in muscle activation u_{i+1} - u_i as a function of the muscle length error e_i is still a sunken, asymmetric "V", albeit noisier, consistent with data.

C. *Continuous-time model of slacking*

The models examined so far have assumed that the motor system controls movements in a discrete fashion; that is, for the i^{th} movement, the motor system selects a feedforward control parameter u_i and measures an error signal e_i. Movement tasks such as target tracking, which are common in therapy applications of robotic orthoses, do not fit well in this paradigm. We previously proposed [12] a simple continuous-time model of slacking during such a task:

$$\dot{u} = -k_h \dot{e} - g_h e - f_h u \quad (5)$$

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 (note that u increases in the direction opposite to e to reduce e). The third term is a slacking term with a forgetting rate $f_h \geq 0$. This term decreases force output when error is zero. We showed previously that this model accurately predicts that people with and without a stroke will allow an arm exoskeleton controlled with an adaptive controller to take over force generation during a target tracking task, unless the robot contains a slacking term [12]. For this experiment, the time constant of human slacking (i.e. $1/f_h$) was about 100 sec [6].

The integral term in Equation 5 is unrealistic for human movement control, as it does not take into account delays between error sensing and force generation. We recently performed an experiment in which we applied vertical step force perturbations of random magnitude to the arm as healthy subjects tried to keep a cursor representing hand position in a target. We obtained good fits to the data (Figure 2) using a model of the following form:

$$M\ddot{e} + B\dot{e} + Ke = F_R + u \qquad (6)$$

That is, the human arm acts like a second order system driven by the force from the robot F_R and the force from the human muscles u. When F_R changes by ΔF_R due to an applied perturbation, we found that a model in which u changes by $-\gamma\Delta F_R$ approximately 500 ms later fits the tracking error history well (Figure 2). The mean of the constant γ was 0.94 +/- 0.034 and is significantly less than 1, (7 healthy subjects, $p < 0.005$, t-test). Thus, the model suggests that the human motor system measures error, and within a 500 ms period, estimates and applies an appropriate force to cancel this error, but slightly underestimates this force. A continuous time model of human slacking is thus:

$$\dot{u} = -f_h u - G(e) \qquad (7)$$

where the slacking rate $f_h \geq 0$ determines the time constant of slacking when error is small, and the update function G represents the process in which the motor system cancels changes in applied, external force 500 ms after they are applied, slightly underestimating the applied force.

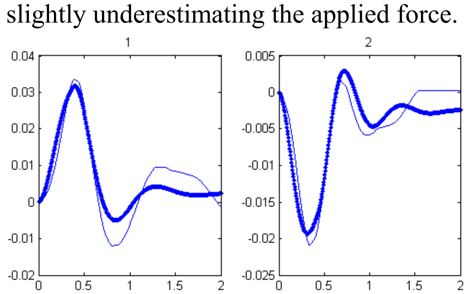

Figure 2. Example fits to experimental data using the model of equation (7). The units of the y-axis are hand position in meters, and that of the x-axis is time in seconds. In this experiment a robotic exoskeleton applied a step force at time 0 to the human arm upward (left) or downward (right). The human arm behaved like a 2nd-order system responding with a change in muscle force equal to the perturbing force, but applied 500 ms later.

III. Consequences of Slacking for Robotic Orthoses

A. Human slacking during robot-assisted therapy

Wolbrecht et al. [6] developed an adaptive controller for a pneumatic arm orthosis that learns the dynamics of the patient's arm, ability and effort at the same time [4]. The device can provide compliant assistance as needed for a patient to actively participate and be able to complete target tracking tasks. They found, however, that both healthy subjects and people with a stroke tended to let the robot take over the task of lifting the arm, unless the robot controller included a slacking term.

Consistent with this finding, Fig. 3 shows data from a recent experiment in which non-disabled subjects tried to hold their hand in a fixed location, and we varied the robot slacking rate. After 30 seconds, the robot began to take over lifting, if the slacking rate was small. The model of Equation 7 predicts this behavior, as shown in Fig. 3.

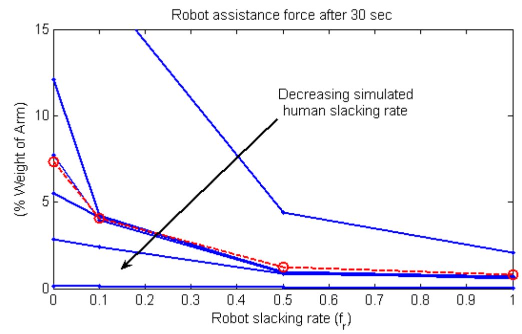

Figure 3. Actual (dashed lines) and modeled (solid lines) human slacking in response to assistance provided by an adaptively controlled robotic arm exoskeleton. The dashed line shows data measured from an experiment in which 7 healthy subjects tried to keep their hand position at a constant location, as a robotic exoskeleton generated assistance forces according to an adaptive algorithm described in [6], with 4 different robot forgetting rates f_r (0, 0.1, 0.5, and 1). The y-axis shows the amount of robot assistance force after 30 seconds. Note that the robot tended to "take over" lifting the arm (and the subject slacked) when the robot forgetting rate was small. The solid lines show results of simulations of the model of Equation 7, with various human forgetting rates (0, 0,001, 0.002, 0.0029, 0.01, 0.1). The model predicts the slacking tendency, with the best fit for f_h = 0.0029, which corresponds to a slacking time constant of 350 s.

B. Learning to be energy efficient in response to an assistive ankle orthosis

Gordon et al. [13] recently showed that healthy human subjects learn to reduce their ankle planar flexor (soleus) muscle activation levels when walking in an orthosis that assists in ankle plantar flexion during stance. We show here that the "sunken V" model of Equation 3 [11] predicts the observed change of muscle activation as stepping proceeded with the orthosis on. The slacking term in the Franklin et al. model is what accounts for the ability of the participants to learn to walk more efficiently with the orthosis.

In this experiment, the ankle orthosis was a carbon fiber exoskeleton powered by an artificial pneumatic muscle working in parallel with the human ankle plantar flexor muscles. The artificial muscle was controlled using a proportional myoelectric control algorithm in which soleus surface EMG was rectified and smoothed (10 Hz cutoff) and used to control the air pressure in the pneumatic muscle.

Figure 3A and 3C show the mean plantar flexor (soleus) and dorsiflexor (tibialis anterior) EMG measured from 10 healthy participants as they walked on the treadmill at 1.25 m/s [13]. The orthosis assistance was turned on at 10 minutes

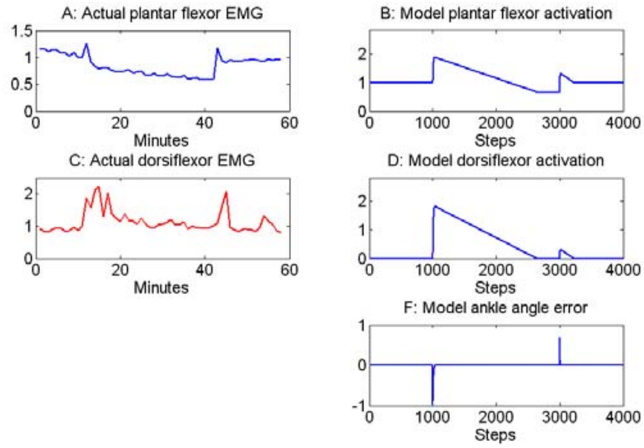

Figure 4: Model of slacking explains adaptation to a robotic ankle exoskeleton. Left: Actual ankle muscle EMG data from [13]. The orthosis power was turned on 13 minutes into stepping, and then off at about 43 minutes. Right: Model predictions for muscle activations using the Franklin et al. [11] sunken "V" model. The human system worked quickly to correct ankle error (F). EMG was normalized to final baseline value.

and then off at about 40 minutes. When it was turned on, both plantar flexor and dorsiflexor EMG increased, indicating co-contraction. Both muscles then slowly decreased activation as the participants continued to step with assistance from the orthosis. When the orthosis assistance was turned off, EMG temporarily increased again. All eight leg muscles measured showed initially increased activity [13], consistent with the use of co-contraction to initially cancel the orthosis perturbation.

Figure 3B and 3D show that the Franklin et al. model can capture the basic features of the evolution of muscle activation. We assumed that the dynamics of the ankle were captured by a linear relationship between the muscle forces and ankle error, which is likely a good assumption at least for small perturbations. The model predicts the initial co-contraction experimentally observed when the orthosis assistance was turned on, followed by a slow decrease in muscle activation, followed by a temporary increase again when the orthosis was turned off. The rate of decrease is determined by how sunken the "V" is, suggesting that the ability of the human participant to learn to walk more efficiently in the orthosis is due to a slacking process.

IV. Discussion

This paper described computational models of slacking and showed how these models predict the human response to assistance forces provided by robotic orthoses. In brief, slacking implements force conservation. For therapeutic applications, this means that slacking will tend to make people relax and let the robotic orthosis do the work, which could have detrimental consequences for use-dependent plasticity. Indeed, it was recently found that people with a spinal cord injury consumed 50% less energy when walking in a relatively rigid gait orthosis as compared to walking with assistance from a physical therapist [14]. Therapeutic training with this gait orthosis was approximately half as effective as training with human therapists for SCI patients who had some initial capability to walk, albeit slowly [15, 16]. Incorporating slacking into control algorithms for robotic therapy devices may help solve this problem [6, 12], as predicted by the computational models developed here.

For force-amplifying orthoses intended to assist people in achieving desired tasks, the fact that slacking implements force conservation is beneficial: it means that people will learn to adapt to the assistance provided by the orthosis, as shown with the simulations presented here. Future research should examine the conditions under which the slacking process would not be expected to produce an optimal energetic response, and then address this potential problem.

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