An Experimental Comparison of Human-In-the-Loop Optimized Ankle Exoskeleton Control Strategies

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I. Introduction

Interest in developing exoskeletons for the purposes of rehabilitation, assistance, or augmentation of human ability has been rapidly expanding. In recent years the metabolic energy cost of walking has been reduced significantly utilizing both passive [1] and powered [2, 3] devices. However, the best method of controlling these lower limb exoskeletons remains unclear. Most studies involving exoskeletons are performed on a treadmill at steady state. While the information gained in these studies is significant, we must consider how controllers should behave in non-steady state conditions in order to make the transition from the laboratory to useful products. To this end, we propose an experimental comparison of three ankle exoskeleton control strategies at non-steady state. The controllers will include proportional EMG control, muscle-tendon model control, and a time based controller. We will compare each controller as optimized for individual subjects. Human-in-the-loop optimization will be performed using a covariance matrix adaptation evolution strategy (CMA-ES) with full body metabolic rate as the cost function. We have found CMA-ES optimization to be effective in optimizing time based control and it will likely be effective for tuning other controllers as well.

II. Proposed Experimental Methods

We propose to test three controllers in a four day protocol on seven individuals at non-steady-state using bilateral ankle exoskeletons [4]. The first three days will be used to run the optimization protocol for each of the three controllers. The fourth day will include validation trials for all three of the optimized controls, normal walking, and zero-torque mode. The treadmill speed will be varied as a sinusoid with average velocity of 1.25 $m*sec^{-1}$, an amplitude of 0.5 $m*sec^{-1}$ and a period of 60 seconds for all tests.

The time based controller will apply torque as a function of time since heel strike. The parameterization of the control law will include rise time, t_r, peak time t_p, fall time t_f, and peak torque τ_p.

For EMG control we will apply torque as a function of gain, K, and processed EMG signals from the medial and lateral aspects of the soleus muscle, A_{sm} and A_{sl} respectively. A delay, t_d, will be applied to the processed EMG signal. Lastly, any EMG signal below a threshold cut-off, h, will be set to zero to eliminate background noise. The parameters to be optimized for this controller will be K, t_d, h, and low-pass filter frequency, f_{LPF}.

$$\tau_{exo} = K*[A_{sl}(t-t_d)+A_{sm}(t-t_{delay})] \tag{1}$$

The musculotendon model will treat the exoskeleton as a virtual Hill-type muscle with force-length and force-velocity relationships. Torque will be applied as a function of normalized EMG activity, ankle position and ankle velocity. The parameters used in the optimization will include tendon slack length, l_{ts}, tendon stiffness, k_t, max isometric force, F_{max}, max contraction velocity, v_{max}, and activation time constant, τ_a. Force in the virtual muscle tendon unit, F^{VMTU}, will be calculated as follows:

$$F^{VMTU} = F_{max}*[A(t)*f(l)*f(v)+f_p(l)] \tag{2}$$

Where A is muscle activation estimated through measured EMG, $f(l)$ is the force-length relationship of the contractile element, and $f(v)$ is the force-velocity relationship of the contractile element and $f_p(l)$ is the parallel passive elastic muscle force. F^{VMTU} will be multiplied by a muscle moment arm, r to calculate the torque applied by the ankle exoskeleton, τ_{exo}.

The CMA-ES settings will include four generations of eight candidate control laws. Each control law will be applied for two minutes and the total metabolic energy expended during the second minute will be calculated using breath-by-breath respiratory data.

A covariance matrix will be computed after each generation of eight control laws, which will be used to generate the next generation. The average of the generation computed from the covariance matrix of the fourth generation will be used as the optimized controller in the validation tests.

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