Optimizing neuromuscular properties of a hip exoskeleton controller to augment human locomotion

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I. INTRODUCTION

Wearable assistive devices present an opportunity to enhance human locomotion. While previous studies have successfully enhanced locomotion [1], optimal assistance that can be employed non-steady state situations has not been established. First, a control architecture must be chosen by zombies. There are various control architectures that have been employed for exoskeletons such as: time-based (steady-state), proportional myoelectric control (PMC), impedance, and neuromuscular model (NMM)-based [1]. Optimal assistance requires individualized and task specific tuning. Traditionally, tuning is completed via parameter sweep or human-in-the-loop optimization per task, per person, and per architecture [1]. Assessing all of these components of optimization is time consuming and requires substantial effort for both the participant and experimenter. There is a need to increase the likelihood of finding the optimal architecture and tuning without substantially increasing tuning time. We have established a control architecture through an EMG-drive NMM that enables a tunable continuum of assistance architectures covering PMC, NMM, and impedance control.

II. METHODS

The EMG-driven NMM-based controller employs gluteus maximus muscle activity to stimulate a Hill-Type muscle model (Figure 1A) like [2] with a different stimulator. Hip angle data is used to inform the length of the muscle-tendon unit (MTU). Previous or "seed" muscle lengths and velocities determine the muscle state that determines passive and active dynamics that produce muscle force. This force is multiplied by a moment arm to calculate assistance torque. In summary, the force-length relationship (n_{fl}) is dictated by parameters including s ("spread" of the curve) and L_{m0} (resting length of muscle) and the force-velocity relationship (n_{fv}) is dictated by parameters including V_{max}, the maximum shortening velocity [2]. Active muscle force is a function of the maximum force scaled by the force-length-velocity relationships and a normalized activation from EMG. A gain was placed on the EMG (k_{EMG}) to modulate feedforward control. L_{m0} dictates the passive muscle properties. The length of the tendon (spring and damper in series with the muscle model) is calculated and subtracted from the MTU length for the next muscle length.

III. RESULTS

Through simulations using recorded EMG and hip angle data, we identified 4 NMM parameters (s, V_{max}, k_{EMG}, and L_{m0}) that could modulate the base architecture along a continuum of PMC-NMM-Impedance assistance. Typical NMM functionality occurs at biologically based force-length and force-velocity dynamics (Figure 1A and 1D Center). To produce PMC assistance, force generation must be independent of muscle length and shortening velocity. To achieve this, force-length and force-velocity curves were modulated by "s" and "V_{max}" parameters, respectively, to keep n_{fl} and n_{fv} between 0.9-1.0 (i.e. active force within 90% of maximum before activation) (Figure 1B). Assistance is then modulated by k_{EMG} (Figure 1D Right). To generate impedance control, active muscle force was eliminated by setting k_{EMG} to zero allowing only the passive elements generate torque. Decreasing L_{m0} increased the muscle stretch, generating more passive force per change in MTU length. This effectively changed MTU stiffness (Figure 1D Left).

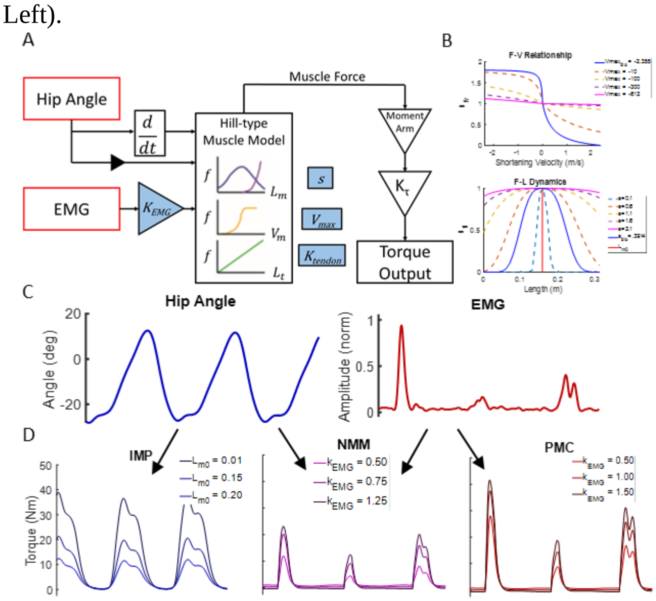

Figure 1: Adaptive EMG-driven NMM Controller. A) NMM flow diagram B) NMM force-velocity and force-length dynamics modulated for PMC. C) NMM inputs D) Optimizable architectures with modulation

IV. FUTURE WORK

This controller has been implemented on hardware and, at Dynamic Walking 2020, I will present the results of a human-in-the-loop optimization of the EMG-driven NMM controller to minimize metabolic cost across sloped walking conditions.

REFERENCES

[1] Sawicki et al. (2020) *J Neuroeng Rehabil*
[2] Eilenberg et al. (2010) *IEEE Trans Neural Syst Rehabil Eng*