2017 International Conference on Rehabilitation Robotics (ICORR)
QEII Centre, London, UK, July 17-20, 2017.

Comparing Neural Control and Mechanically Intrinsic Control of Powered Ankle Exoskeletons

Jeffrey R Koller*,1, C David Remy[1], *Member, IEEE*, and Daniel P Ferris[2]

Abstract— **There are an infinite number of ways to control an assistive robotic device; however, there is little consensus on which ways are better than others and why. We designed this study to compare the control of powered ankle exoskeletons using neural measurements to drive control versus that using mechanically intrinsic measurements. The controller driven by neural measurements was a dynamic gain proportional myoelectric controller using user's soleus muscle activity for an actuation signal. The controller driven by mechanically intrinsic measurements was a timing-based controller using detected heel-strikes of the user to appropriately time actuation. We designed these two controllers in such a way that both had the same average actuation signal and tested them with 8 healthy subjects. Results show no significant difference in metabolic work rate between the two controllers. Both controllers resulted in reductions in metabolic work rate of 19% below walking in the devices unpowered. We found that subjects using the timing-based mechanically intrinsic controller exhibited less positive and negative total ankle power than when using the dynamic gain proportional myoelectric controller. This finding was coupled with a reduction of 11.8% in soleus muscle activity. We believe these finding can have large implications for applications in rehabilitation and lend insight to when one controller is more appropriate to use than another.**

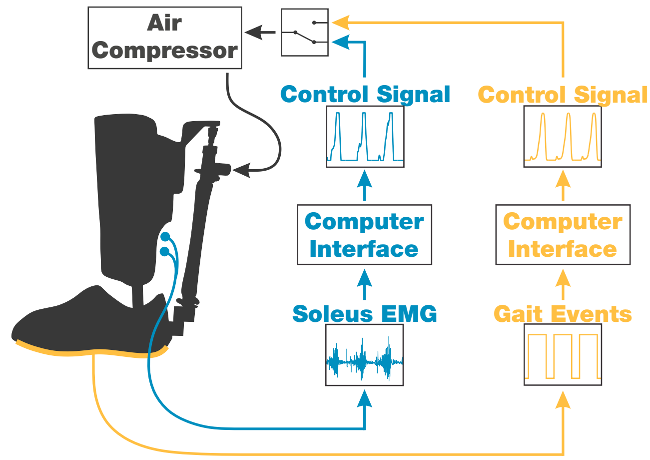

Fig. 1. In this study we conducted a systematic comparison of two controllers: a proportional myoelectric controller (blue) and a timing-based mechanically intrinsic controller (yellow). The proportional myoelectric controller used a dynamically adjusting gain to map users' peak soleus muscle activity to maximal actuation output. The actuation signal for the timing-based mechanically intrinsic controller was designed on a subject-specific basis as the average control signal from each user's walking bout using the proportional myoelectric controller. In doing so, the two controllers had the same average control signal, but one was directly driven by the user's muscle activity while the other was driven by measured gait events.

I. INTRODUCTION

Lower extremity assistive robotic devices perform mechanical work in parallel with the user during walking. These devices are designed with the intention of aiding the user in locomotion; however, their success in doing so is highly dependent upon their controller design. With the proper controller design, a device has the potential to reduce the required biological energetic input from the user during walking [1]. With the improper controller design, a device can hinder the user's locomotion causing a suboptimal decrease in biological energetic input or potentially an increase in energy expenditure [2]. This leads to the challenging question of "how does one best control an assistive robotic device?" Given the infinite number of possible controller designs, this is a very difficult question to answer.

From a broad perspective on the field of lower extremity assistive device control, there are two primary categories of controller designs: those driven by neural measurements and those driven by mechanically intrinsic measurements. Controllers driven by neural measurements rely on measures of electrical activity from the body's nervous system to directly drive control. These measures may be of the user's brain activity, which is sensed using electroencephalogram (EEG) electrodes on the head, or of the user's muscle activity, which is sensed using electromyography (EMG) electrodes probed directly into the muscle or on the skin's surface [3], [4]. Controllers driven by mechanically intrinsic measurements rely on measurements taken from the device itself such as joint angles, actuation power output, or gait events. These signals may be used as phasing variables within a control scheme or as triggers for a timing-based controller [5].

Devices driven by neural measurements and devices driven by mechanically intrinsic measurements each have their own pros and cons. Neural control is often thought to have a theoretical synchronization advantage over controllers driven by mechanically intrinsic measurements [6]. This is because neural signals can be measured before movement has actually occurred since electrical activity in the body can be sensed prior to actual force generation by the muscles [7]. This electromechanical delay implies that controllers driven by neural signals have the potential to move in perfect unison with the user. In contrast, mechanically intrinsic measurements can only be sensed after movement has already occurred therefore always lagging behind the user's movement. Additionally, if the actuation of a device is proportional to the driving neural measurements, the user can

*Corresponding Author: jrkoller@umich.edu
[1]Department of Mechanical Engineering, University of Michigan, Ann Arbor, MI
[2]School of Kinesiology, University of Michigan, Ann Arbor, MI
This work was financially supported by funds from a U.S. Department of Defense Grant (W81XWH-09-2-0142) and a University of Michigan Rackham Graduate Student Research Grant.

directly control the timing and amplitude of actuation at any time instance using the same means of neurological control they would adjust their own muscle contraction timing and amplitude. This leads to a more natural means of control and adaptation over a controller driven by mechanically intrinsic measurements [8]. One major advantage of devices driven by mechanically intrinsic measurements over those driven by neural measurements is the reduced complexity. With a controller driven by mechanically intrinsic measurements, all sensors can be self contained in the device; however, when using neural measurements, electrodes need to be appropriately fitted and placed on the user. Additionally, the current means of sensing neural measurements tend to lead to very noisy signals that can be difficult to decode or filter in real time.

Despite the prevalence of these two broad categories of controller design, to date, there exists no systematic and fair comparison of which may be better to use on a device and why. There have been some high level comparisons, but these studies were not designed to accurately tease out the true differences in the controllers or their physiological and biomechanical effects on the users. Cain et al. [8] conducted a study comparing proportional myoelectric control of a unilateral ankle exoskeleton to that of a timing-based controller, and Zhang et al. [9] conducted a study with bilateral ankle exoskeletons where 34 different control strategies, some of which were variations on proportional myoelectric control, were compared to one another. In both of these studies there were a number of variables, such as actuation signal shape and timing, that were different between the controllers making it difficult to draw definitive conclusions about how a controller driven by neural measurements may differ from a controller driven by mechanically intrinsic measures.

In the work presented here, we aimed to make a systematic comparison between a proportional myoelectric controller and a timing-based mechanically intrinsic controller for bilateral ankle exoskeletons (Fig. 1). We created the actuation profile for the timing-based controller directly from the average of control signals seen during use of the proportional myoelectric controller. By doing so we ensured that the two controllers had the same average actuation signal. The only difference in the two controllers was that one was driven directly by the users' muscle activity while the other was driven by measured gait events. We have tested both controllers on a healthy subject population during treadmill walking. We have calculated a number of physiological and biomechanical outcomes to compare these two controllers to see if there are any major difference in the two, lending insight into when one may be of better use than another.

II. MATERIALS AND METHODS

A. Subjects

We tested 8 healthy subjects for this study (male, 21 $\pm$ 1 years, 74.0 $\pm$ 2.7 kg, 180.0 $\pm$ 2.8 cm; means $\pm$ s.e.m.). Subjects exhibited no gait abnormalities and had no experience walking in powered exoskeletons prior to this study. Prior to testing, all subjects gave informed written consent to participate in the study in accordance to the University of Michigan Medical School's Institutional Review Board.

B. Exoskeleton Hardware

We custom fabricated bilateral ankle exoskeletons for this study that were comprised of a shank and shoe component. The shank component consisted of plastic cuffs and metal rods. We included ratchet straps on the cuffs to allow for a custom fit on a subject-specific basis. The shoe component was a standard orthotic shoe with embedded metal components to allow for the attachment of actuation. The shank and shoe components were joined by a single rotational joint that constrained the device to plantar flexion and dorsiflexion. We actuated the exoskeletons to aid in plantar flexion by attaching custom built artificial pneumatic muscles posterior to the device [10]. A more detailed description of the exoskeletons can be found in [11] and a line drawing of one of the devices is shown in Fig. 1.

C. Exoskeleton Control

For this study we aimed to compare two different types of controllers to be used on the same exact hardware. Both controllers were custom built in Simulink (The MathWorks, Inc., Natick, MA) and converted to run on a real-time control board (dSPACE, Inc., Northville, MI).

1) Dynamic Gain Proportional Myoelectric Control: We designed the proportional myoelectric controller to be driven by EMG activity of the user's soleus muscle. We measured subjects' soleus activity in real-time using EMG surface electrodes (sample rate: 1000 Hz; Biometrics, Ladysmith, VA). The designed controller then processed this raw signal into its linear envelope. This processing consisted of a high-pass filter (2nd order Butterworth, cutoff frequency 80 Hz) to remove motion artifacts, followed by fullwave rectification. The rectified signal was then low-pass filtered (2nd order Butterworth, cutoff frequency 4 Hz) to achieve the linear envelope.

The controller multiplied this linear envelope by a gain in order to linearly map the small voltage of the processed EMG signal into a larger control voltage that was sent to the pressure control valves used to actuate the exoskeleton. The gain used for this linear mapping was tuned continuously on a subject-specific basis using a dynamically adaptive algorithm as described in [11]. This algorithm continuously tuned the gain such that the average peak EMG signal over the previous 50 strides mapped to a desired maximum control signal voltage. In this case, we chose the maximum voltage that allowed for the maximum output pressure by the valves. This created a controller that, on average, always output maximal peak actuation from the device at the moment when the average maximal peak muscle activity of the soleus was measured.

2) Timing-Based Mechanically Intrinsic Control: We designed the timing-based mechanically intrinsic controller to have the same average actuation signal as that of the proportional myoelectric controller. To do so, we normalized the actuation signals from the final 100 strides of a subject's walking bout using the proportional myoelectric controller by their percent gait cycle. We then averaged these 100 actuation signals and calculated the root mean squared error (RMSE) for each stride's actuation signal compared to the average. We discarded the strides with the top 20% of RMSE values in order to safely remove any outliers. The remaining strides' actuation signals were then averaged to compose the actuation signal for the timing-based mechanically intrinsic controller. This whole process was done separately for each individual subject and leg.

During walking, the timing-based mechanically intrinsic controller simply played back the calculated average actuation signal with each heel strike. This process was similar to pressing a "play" button on a prerecorded signal with each heel strike. Heel strikes were detected using the force plates in the instrumented treadmill. If a stride was shorter than the averaged control signal, the signal would start over immediately. If a stride was longer than the averaged control signal, the actuators remained at a pressure that resulted in zero force generation until the next heel strike.

D. Testing Protocol

For this study, all subjects were trained to walk with powered bilateral ankle exoskeletons using a dynamic gain proportional myolelectric controller by participating in 3 separate training sessions. During these training sessions, subjects walked continuously in the exoskeletons for 50 minutes, the middle 30 of which were powered. A more detailed description of these sessions is described in [11].

After completing the 3 training sessions, subjects returned for a 4th day of testing. During this testing session, subjects participated in 4 different walking bouts all at 1.2 m/s on an instrumented treadmill (Bertec Corporation, Columbus, OH). Each walking bout was 10 minutes long with a 5-10 minute seated resting period between each bout. The 1st bout was simply an unpowered condition where subjects walked in the exoskeletons with no actuation. The 2nd bout was using the dynamic gain proportional myoelectric controller. The 3rd bout was using the timing-based mechanically intrinsic controller where the actuation signal was calculated using the final 100 strides from the previous bout. The 4th bout was using the dynamic gain proportional myoelectric controller for a second time. The proportional myolectric controller was used in both bouts 2 and 4 to check for continued learning effects. The focus of this study was to compare walking bouts 3 and 4. Bouts 1 and 2 are included in all results for reference to show that the exoskeletons are having an effect on the users and that no learning effects are occurring during testing. These two bouts have subsequently been faded into the background on all resulting figures as they are not the primary focus of the study.

E. Measurements and Analysis

During testing we measured O_2 and CO_2 flow rates using a portable open-circuit indirect spirometry system (CareFusion Oxycon Mobile, Hoechberg, Germany). We converted these measurements into measures of metabolic work rate using formulas from Brockway [12]. Prior to the first walking bout, we recorded a 3 minute standing trial from each subject. We averaged over these 3 minutes to calculate each subject's standing metabolic work rate. This standing measure was then subtracted from each walking bout to calculate the net metabolic work rate [13]. We analyzed each walking bout by averaging the metabolic work rate over the final 3 minutes and then normalized it by subjects' body mass. During testing, we monitored subjects' respiratory exchange ratio (RER) to ensure that it remained in the aerobic range (RER$<$1) [14].

We measured joint kinematics and kinetics during treadmill walking using a 10-camera motion capture system (sample rate: 100 Hz; Vicon, Oxford, UK) and a split-belt instrumented treadmill. We measured kinematics using a 39 reflective markers set (34 on the pelvis and lower limbs, 4 on the torso, and 1 on the head). All joint kinematics and dynamics were calculated from raw marker data using OpenSim 3.2 [15]. We calculated joint power by multiplying joint torque by joint angular velocity. Average positive, negative, and net power were calculated for each stride by integrating the positive, negative, and net power values, respectively, and dividing them by the corresponding stride time. All joint measure results represent averages from each subject across the final 25 strides of both legs during the final minute of each walking bout.

We measured users' soleus activity from each leg using bipolar surface electrodes (sample rate: 1000 Hz; Biometrics, Ladysmith, VA) with an inter-electrode distance of 2.0 cm and electrode diameter of 1.0 cm. The EMG amplifier had a bandwidth of 20-460 Hz. We post-processed the EMG data into its linear envelope by high-pass filtering (3rd order Butterworth, zero-lag, 35 Hz cut-off frequency), full-wave rectifying, and then low-pass filtering (3rd order Butterworth filter, zero-lag, 10 Hz cut-off frequency) the raw data. We then normalized each stride corresponding to subject-specific average peak voltage from the unpowered walking bout. The linear envelopes from the final 25 strides were then averaged for each individual subject prior to averaging across subjects. We additionally calculated the average stride root mean square (r.m.s.) for the rectified EMG signals. The r.m.s. calculations were normalized by the average r.m.s. value from the unpowered walking bout prior to averaging the final 25 strides for each individual subject. Individual subject averages were then averaged across subjects.

All data were analyzed across walking bouts using a repeated measures ANOVA analysis ($\alpha = 0.05$).

III. RESULTS

Resulting averages in metabolic work rate across subjects are shown in Fig. 2. The 1st walking bout with the dynamic gain proportional myoelectric controller resulted in a reduction in metabolic work rate relative to the unpowered walking bout of 0.59 ± 0.12 W kg^{-1} ($15.1 \pm 2.3\%$, mean $\pm$ 1 s.e.m.). The timing-based mechanically intrinsic controller resulted in a reduction in metabolic work rate relative to the unpowered walking bout of 0.73 ± 0.13 W kg^{-1}

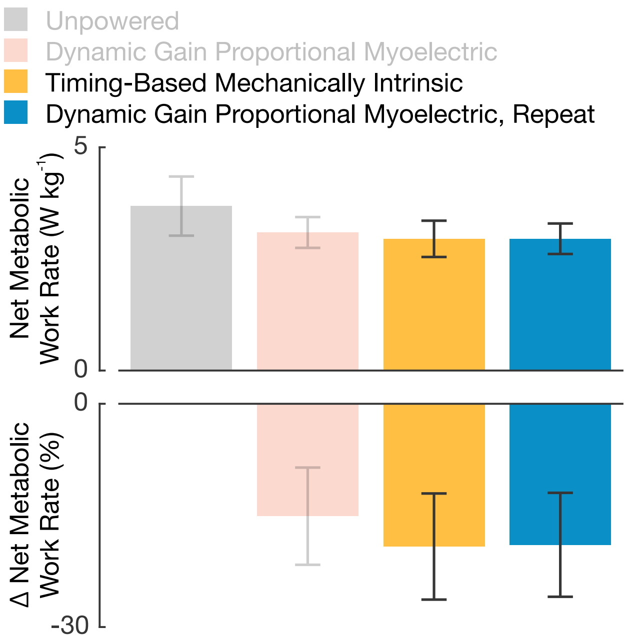

Fig. 2. Average metabolic results (mean $\pm$ 1 s.e.m.) from the 4 walking bouts across 8 subjects. The main purpose of this study was to compare neural control and mechanically intrinsic control of ankle exoskeletons. For that reason, the first two walking bouts are faded into the background for reference. The difference in means of the metabolic results across all walking bouts were statistically different from zero ($p = 0.018$). The difference in means of the metabolic results between the 2nd dynamic gain proportional myoelectric controller walking bout and the timing-based mechanically intrinsic controller walking bout is not statistically different from zero ($p = 1.000$).

($19.2 \pm 2.5\%$). The 2nd walking bout with the dynamic gain proportional myoelectric controller resulted in a reduction in metabolic work rate relative to the unpowered walking bout of 0.73 ± 0.13 W kg^{-1} ($19.0 \pm 2.5\%$). The difference in mean metabolic work rate across all walking bouts were significantly different from zero ($p = 0.018$), showing that powering the exoskeletons resulted in a significant reduction in users' energetic demand. Statistical analysis also shows that the subjects' mean metabolic work rate during powered walking bouts were not significantly different from one another (all $p > 0.05$). This result allows us to make two conclusions: 1) subjects were fully trained in using the devices as there were no learning effects present between the two bouts of using the proportional myoelectric controller and 2) there was no metabolic difference between using the proportional myoelectric controller and using the timing-based mechanically intrinsic controller. For this reason, all comparisons between controllers from this point forward will be drawn from the walking bout using the timing-based mechanically intrinsic controller and the 2nd walking bout using the dynamic gain proportional myoelectric controller.

Resulting averages in total ankle power (exoskeleton plus biological ankle power) across subjects are shown in Fig. 3. The difference in means of average positive, negative, and net total ankle power across all walking bouts were significantly different from zero ($p < 0.001$, $p = 0.016$, and $p < 0.001$, respectively). The magnitudes of average positive and negative total ankle power during walking with the timing-based mechanically intrinsic controller were significantly less than during the 2nd walking bout with the dynamic gain proportional myoelectric controller ($p = 0.029$ and $p = 0.008$, respectively). There was no significant difference in means of the average net total ankle power between these two same conditions ($p = 1.000$).

Resulting averages in soleus muscle activity across subjects are shown in Fig. 4. The difference in means of soleus r.m.s. EMG were significantly different from zero across all walking bouts ($p < 0.001$). Although the difference in means of soleus r.m.s. EMG activity were not significantly different between the timing-based mechanically intrinsic controller and the 2nd walking bout with the dynamic gain proportional myoelectric controller ($p = 0.793$), there was a decreasing trend in the averages across controllers. The soleus r.m.s. EMG during walking with the timing-based mechanically intrinsic controller was on average 11.8% less than during the 2nd walking bout with the dynamic gain proportional myoelectric controller. This decrease in average EMG activity is clearly visible in the linear envelopes (Fig. 4A).

IV. DISCUSSION AND CONCLUSION

In this study we aimed to identify if there were any biomechanical and physiological differences to using an exoskeleton driven by neural measurements versus mechanically intrinsic measurements. We achieved this by comparing the control of bilateral ankle exoskeletons using a dynamic gain proportional myoelectric controller to a timing-based mechanically intrinsic controller. In doing so, we designed the two controllers to have the same average actuation control signal meaning the only difference between the two controllers were the signals by which actuation was triggered. We showed that the two controllers had no significant difference in metabolic work rate ($p = 1.000$), indicating that there is no energetic benefit to one over the other. However, there were some differences in biomechanics.

First, we found that subjects used less average positive and negative total ankle power ($p = 0.029$ and $p = 0.008$, respectively) with the timing-based mechanically intrinsic controller than with the dynamic gain proportional myoelectric controller. In an attempt to uncover where the decrease in power was coming from, we looked at the muscle activity about the ankle. From the EMG analysis, we showed that when subjects were using the timing-based mechanically intrinsic controller they had less muscle activity than when using the dynamic gain proportional myoelectric controller. This was made evident by both the linear envelopes and the r.m.s. EMG results (Fig. 4A and 4B, respectively). Although the decrease in r.m.s. EMG was not statistically significant across all 8 subjects ($p = 0.793$), there was a decreasing trend between the two controllers. Of the 8 subjects tested, 1 showed no difference in mean r.m.s. EMG activity between the controllers and another showed an increase. These results could explain the lack of statistical significance between controllers, while still establishing a prominent trend. The remaining 6 subjects that did show this decreasing trend

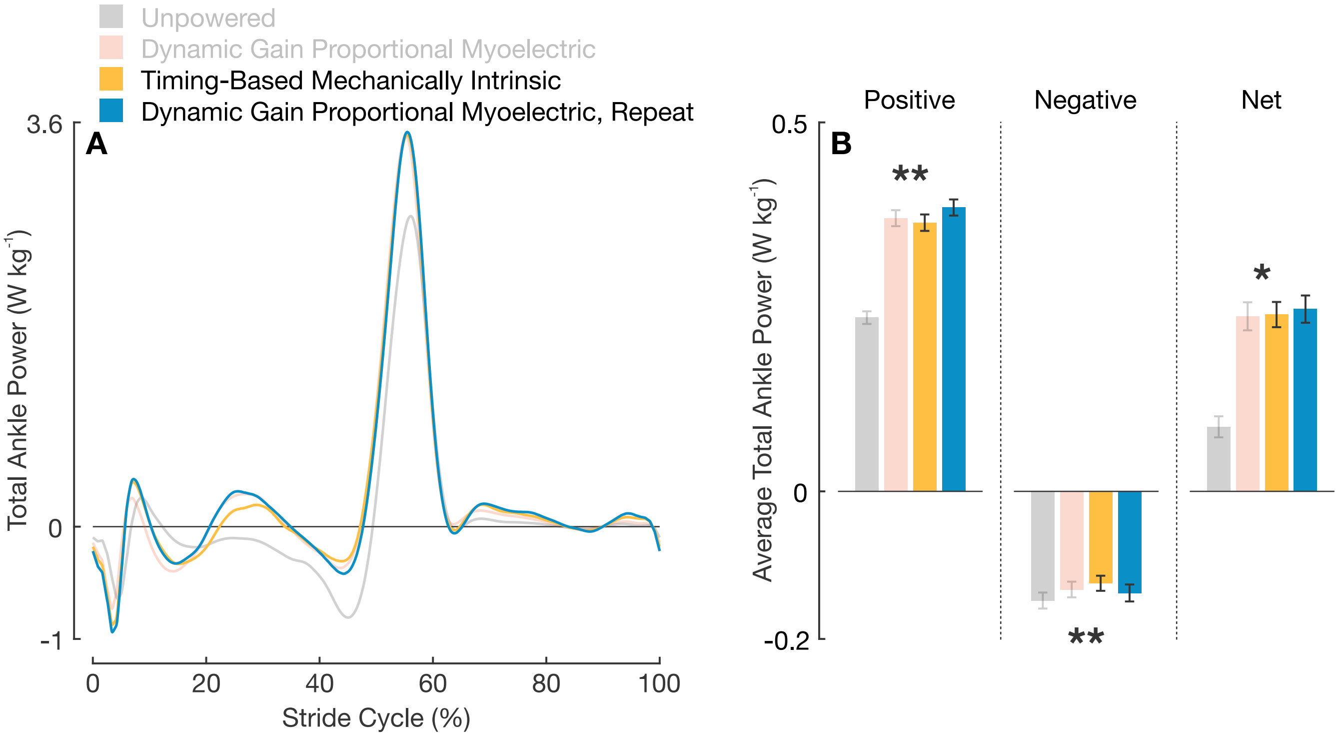

Fig. 3. **(A)** Total ankle power (exoskeleton plus biological ankle power, mean) results from the 4 walking bouts across 8 subjects normalized by stride time. **(B)** Average positive, negative, and net ankle power results. A single asterisk above a bar graph signifies a statistically significant difference in means across the set of 4 walking bouts. A double asterisk above a bar graph signifies the same as a single asterisks in addition to a significant difference in means between the timing-based mechanically intrinsic controller and the 2nd walking bout with the dynamic gain proportional myoelectric controller.

had anywhere from a $4.7 - 37.9\%$ reduction in soleus r.m.s. EMG activity. If we remove the two non-responders from the ANOVA analysis, the difference in the two means are still not significantly different from zero, but they are much closer to being so ($p = 0.067$). In the future, it might be worth exploring this effect and the role of responders and non-responders with a greater sample size of subjects.

The combination of the total ankle power and soleus EMG results suggest that users are putting forth less biomechanical effort at the ankle when using the timing-based mechanically intrinsic controller than when using the dynamic gain proportional myoelectric controller. This is logical as the proportional myoelectric controller simply will not actuate if the user is not actively engaging their soleus muscle. With the mechanically intrinsic controller, the actuation will trigger so long as a heel strike occurs, causing less of an incentive for the user to be actively engaged on a muscular level and thus explaining the observed reduction in EMG activity.

We interpret these results as subjects slacking in their effort when using a controller driven by mechanically intrinsic measurements. The premise behind slacking is that the human motor system continuously attempts to decrease its levels of muscle activation when movement error is small during repetitive motion, such as walking [16]. One hypothesis for interpreting the soleus EMG results of this study is that when users are using the dynamic gain proportional myoelectric controller, they can only slack so far. As the user decreases their soleus EMG, the dynamically adjusting gain will increase to compensate. This increase in the mapping gain would cause for an amplification in any unintended EMG activation spikes. These spikes will become more prevalent as soleus activity is reduced since the reduction causes a decrease in the signal-to-noise ratio. This combination of changing gain and changing muscle activity essentially makes the system more sensitive to noise. Therefore, we hypothesize that subjects can only slack to a certain extent before the increased sensitivity causes complications with users' walking stability. When using the timing-based mechanically intrinsic controller, the actuation is consistently the same for each step, so users can potentially reduce their EMG activity further than with the dynamic gain proportional myoelectric control.

A couple interesting findings can be drawn for this hypothesis of slacking and the shown results. One finding is that because subjects were able to decrease their muscle activity further with the timing-based mechanically intrinsic controller, one would expect that users could theoretically further reduce their metabolic work rate when using a device driven by mechanically intrinsic measurements than with a device driven by neural measurements. This is, however, only assuming straight and continuous walking on level ground. These results may vary when intent recognition is involved for different tasks. We believe that we did not see any metabolic benefit of the timing-based mechanically intrinsic controller over the dynamic gain proportional myoelectric controller because the shown decrease in muscle activity was relatively small. Another interesting finding comes from the idea of increased active involvement (i.e. muscle activity)

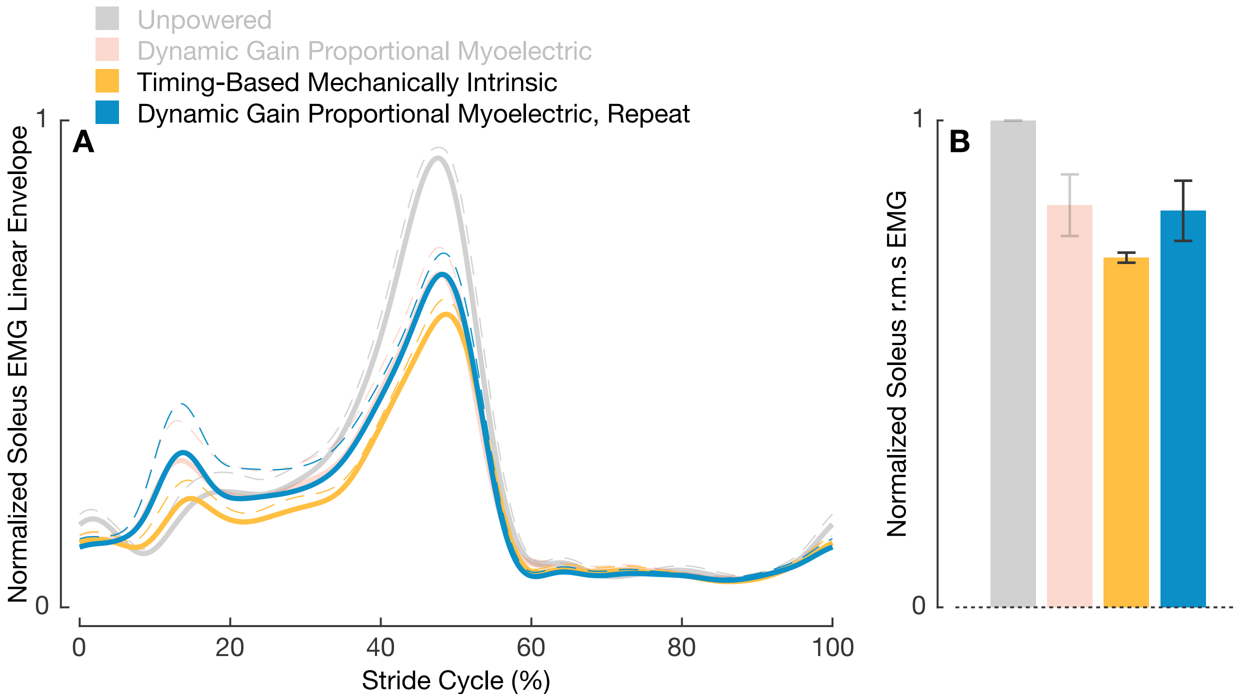

Fig. 4. Average soleus EMG activity from the 4 walking bouts across 8 subjects. **(A)** The linear envelopes were all normalized to subject-specific peak amplitudes of their unpowered walking bout prior to averaging. The dotted lines represent a single s.e.m. above the mean. **(B)** The r.m.s. values were all normalized to subject-specific average r.m.s. values of the unpowered walking bout prior to averaging. The error bars represent the mean $\pm$ 1 s.e.m.

when using a controller driven by neural measurements over that of mechanically intrinsic measurements. This suggests that a neurally controlled device could potentially better benefit rehabilitation than one driven by mechanically intrinsic measurements. This suggestion is drawn from the success of rehabilitation with human therapists being more successful than that with robotic devices in patients with chronic stroke due to patients' active involvement [17]. It is worth noting that the study presented here only considered healthy subjects so further research would need to be conducted with a clinical population to draw definitive conclusions on this.

References

[1] P. Malcolm, W. Derave, S. Galle, and D. De Clercq, "A simple exoskeleton that assists plantarflexion can reduce the metabolic cost of human walking," *PloS one*, vol. 8, no. 2, p. e56137, 2013.
[2] R. W. Jackson and S. H. Collins, "An experimental comparison of the relative benefits of work and torque assistance in ankle exoskeletons," *Journal of Applied Physiology*, vol. 119, no. 5, pp. 541–557, 2015.
[3] A. Kilicarslan, S. Prasad, R. G. Grossman, and J. L. Contreras-Vidal, "High accuracy decoding of user intentions using eeg to control a lower-body exoskeleton," in *2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2013, pp. 5606–5609.
[4] N. Hogan, "A review of the methods of processing emg for use as a proportional control signal." *Biomedical engineering*, vol. 11, no. 3, pp. 81–86, 1976.
[5] R. Jimenez-Fabian and O. Verlinden, "Review of control algorithms for robotic ankle systems in lower-limb orthoses, prostheses, and exoskeletons," *Medical engineering & physics*, vol. 34, no. 4, pp. 397–408, 2012.
[6] A. Young and D. Ferris, "State-of-the-art and future directions for robotic lower limb exoskeletons," 2016.
[7] P. R. Cavanagh and P. V. Komi, "Electromechanical delay in human skeletal muscle under concentric and eccentric contractions," *European Journal of Applied Physiology and Occupational Physiology*, vol. 42, no. 3, pp. 159–163, 1979.
[8] S. M. Cain, K. E. Gordon, and D. P. Ferris, "Locomotor adaptation to a powered ankle-foot orthosis depends on control method," *Journal of NeuroEngineering and Rehabilitation*, vol. 4, no. 1, p. 1, 2007.
[9] J. Zhang, C. C. Cheah, and S. H. Collins, "Experimental comparison of torque control methods on an ankle exoskeleton during human walking," in *2015 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2015, pp. 5584–5589.
[10] D. P. Ferris, J. M. Czerniecki, B. Hannaford, and U. of Washington, "An ankle-foot orthosis powered by artificial pneumatic muscles," *Journal of Applied Biomechanics*, vol. 21, no. 2, p. 189, 2005.
[11] J. R. Koller, D. A. Jacobs, D. P. Ferris, and C. D. Remy, "Learning to walk with an adaptive gain proportional myoelectric controller for a robotic ankle exoskeleton," *Journal of NeuroEngineering and Rehabilitation*, vol. 12, no. 1, p. 1, 2015.
[12] J. Brockway, "Derivation of formulae used to calculate energy expenditure in man." *Human nutrition. Clinical nutrition*, vol. 41, pp. 463–471, 1987.
[13] T. M. Griffin, T. J. Roberts, and R. Kram, "Metabolic cost of generating muscular force in human walking: insights from load-carrying and speed experiments," *Journal of Applied Physiology*, vol. 95, pp. 172–183, 2003.
[14] G. A. Brooks, T. D. Fahey, T. P. White *et al.*, *Exercise physiology: Human bioenergetics and its applications.* Mountain View: Mayfield Publishing Company, 1996.
[15] S. L. Delp, F. C. Anderson, A. S. Arnold, P. Loan, A. Habib, C. T. John, E. Guendelman, and D. G. Thelen, "Opensim: open-source software to create and analyze dynamic simulations of movement," *Biomedical Engineering, IEEE Transactions on*, vol. 54, pp. 1940–1950, 2007.
[16] D. J. Reinkensmeyer, O. M. Akoner, D. P. Ferris, and K. E. Gordon, "Slacking by the human motor system: computational models and implications for robotic orthoses," in *Engineering in Medicine and Biology Society, 2009. EMBC 2009. Annual International Conference of the IEEE*. IEEE, 2009, pp. 2129–2132.
[17] T. G. Hornby, D. D. Campbell, J. H. Kahn, T. Demott, J. L. Moore, and H. R. Roth, "Enhanced gait-related improvements after therapist-versus robotic-assisted locomotor training in subjects with chronic stroke," *Stroke*, vol. 39, no. 6, pp. 1786–1792, 2008.