A benchtop biorobotic platform for *in vitro* observation of muscle-tendon dynamics with parallel mechanical assistance from an elastic exoskeleton

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1. Introduction

Due to rapid advances in batteries, actuators, and wearable sensors, the promise of robotic exoskeletons to restore or augment human locomotion is coming to fruition (Ferris, 2009). In recent years, we have seen rapid development of exoskeletons for use within (Caputo and Collins, 2014; Ferris and Lewis, 2009; Hocoma; Malcolm et al., 2013) and beyond (Elliot et al., 2013; Hasegawa and Ogura, 2013; Kawamoto et al., 2003; Mooney et al., 2014; Wehner et al., 2013; Wiggin et al., 2011; Zoss et al., 2006) laboratory/clinical settings. Unfortunately, the physiological benefit to the user has not progressed as rapidly, and there are only a handful of reports demonstrating reduced metabolic energy cost with a wearable locomotion assistance device (Collins et al., 2015; Malcolm et al., 2013; Mooney et al., 2014; Panizzolo et al., 2016).

A major barrier to uncovering how metabolic benefit is derived from an assistive exoskeleton is understanding the influence of external torques on underlying muscle function. Experimental methods that use hopping as a model of bouncing gait in combination with electromyography, ultrasound imaging, and inverse dynamics can give insight into how and why muscle forces change when working in parallel with an exoskeleton (Farris et al., 2013). Unfortunately, these physiological measurements are difficult to make alongside devices designed to be in close contact with the limb, and few studies of exoskeleton assisted locomotion are accompanied by the instrumentation necessary for in depth understanding of alterations in muscle-level function.

Despite these difficulties, a common theme has emerged from studies of exoskeleton assisted hopping: external application of force in parallel with a compliant muscle-tendon unit (MTU) can disrupt ‘tuned’ muscle-tendon interaction dynamics critical during steady, rhythmic locomotion. Previous studies have observed that humans prefer to keep their joint and limb-level mechanics constant when wearing assistive or resistive devices (Chang et al., 2017).
2008; Kao et al., 2010), that assistive devices lead to a reduction in force produced in contractile elements (CE, i.e., active muscle) of the biological MTU (Farris et al., 2013; Farris and Sawicki, 2012), and that the amount of energy that can be stored/returned in series elastic elements (SEE, e.g., tendon, aponeurosis) is reduced (Farris et al., 2013).

The ability to cycle a portion of center of mass energy in elastic tissues has been identified as a mechanism for reducing energetic demands and enhancing efficiency of gait (Roberts and Azizi, 2011). Despite evidence that elastic exoskeletons disrupt ‘tuned’ muscle-tendon interactions, they can still provide net metabolic benefit for the user (Collins et al., 2015; Farris et al., 2013; Grabowski and Herr, 2009). Interestingly, metabolic benefit does not scale directly with the exoskeleton spring stiffness, and there is compelling evidence that too much assistance (i.e. a device that is too stiff) can actually increase metabolic demands beyond levels required for unassisted movement (Farris and Sawicki, 2012; Grabowski and Herr, 2009). Simple models have provided some insight into this phenomenon, and predicted limits on energetic benefits as a function of device stiffness, measurable physiological properties of the limb, and performance goals (Robertson et al., 2014; Robertson and Sawicki, 2014; Sawicki and Khan, 2016).

Simulations of exoskeleton-human interaction based on simple Hill-type muscle models provide meaningful insight, but cannot capture all aspects of muscle force production (e.g., history dependence) (Josephson, 1999) that are relevant when considering sub-maximal eccentric contractions common in exoskeleton assisted locomotion (Farris et al., 2013). To eliminate reliance on limited muscle models in a simulation framework, we developed a novel benchtop bio-robotic platform to mimic the *in vivo* mechanical environment of muscle-tendon during cyclic contractions (i.e., hopping) with or without exoskeleton assistance. We also implemented a neural controller based on rate coding that can reliably stimulate biological muscle over a range of activation levels (Stevens, 1996).

Using model predictions (Robertson et al., 2014) and a modified version of the novel biorobotic experimental framework from a previous study (Robertson and Sawicki, 2015), we identified appropriate combinations of muscle activation/exoskeleton stiffness to mimic human behavior during hopping with elastic assistance on the benchtop. We hypothesized that assistance from an elastic exoskeleton would: (H1) reduce forces in the biological muscle-tendon unit (MTU); (H2) reduced biological forces and tendon strains would result in increased muscle fascicle shortening velocities; and (H3) reduced biological forces and increased muscle shortening velocities would result in constant average muscle positive mechanical power output. Finally, we postulated that (H4) the combination of these outcomes would ultimately result in a constant system stiffness across both assisted and unassisted conditions.

2. Methods

2.1. Animal subjects and surgical preparation

This study was performed in accordance with protocols approved by the NC State Institutional Animal Care and Use Committee (IACUC). Surgical procedures used here have been previously described in detail (Robertson and Sawicki, 2015). In brief, five adult Rana Lithobates bullfrogs were euthanized, a hind limb was removed and the plantaris-Achilles tendon MTU was isolated. The Achilles tendon was freed from its distal insertion point, while the plantaris attachment at the calcaneus was left intact and portions of femur and tibia were used to anchor the MTU to the benchtop. We hypothesized that assistance from an elastic exoskeleton (modeling an elastic element) of the biological MTU (Farris et al., 2013; Farris and Sawicki, 2012), would result in increased muscle fascicle shortening velocities; and (H3) reduced biological forces and increased muscle shortening velocities would result in constant average muscle positive mechanical power output. Finally, we postulated that (H4) the combination of these outcomes would ultimately result in a constant system stiffness across both assisted and unassisted conditions.

2.2. Motor controller

The motor controller was a modified version of the one used to simulate an inertial/gravitational load in a previous study (Roberson and Sawicki, 2015). We added a parallel elastic exoskeleton to mechanical environment simulations using the approach outlined in a prior computer simulation study (Robertson et al., 2014) (Fig. 1A). Details of motor controllers and implementation can be found in Supplementary methods.

2.3. Muscle stimulation controller

We used a `pulsed` rate coding approach to modulate force/activation as described in Stevens (Stevens, 1996). Using an assumed experimental driving frequency ($\omega_{drive}$) of 2 Hz (discussed in detail below), and a set stimulation duty of 10% of a driving cycle (i.e., $T_{d} = 0.1 \times \omega_{drive}^{-1} = 50$ ms), we performed a small study (n = 3) to determine the influence of $\omega_{drive}$ on peak force ($F_{peak}$) output (Fig. 1B). The muscle preparation was the same as those detailed above, except the free tendon was clamped at the muscle tendon junction to minimize shortening against series connective tissues. The ergometer arm was set to a fixed position for which passive muscle force was ~1 N, and the muscle was subjected 5 experimental conditions consisting of 3 consecutive contractions ($\omega_{drive} =$ 2 Hz, $T_{d} =$ 50 ms) with $\omega_{drive}$ values of 20, 40, 60, 80, and 100 Hz (i.e., 8 spikes/pulse = 1, 2, 3, 4, and 5, respectively). Based on previous research, we assumed that $\omega_{drive}$ of 100 Hz resulted in maximal muscle activation (Pennycook, 1964; Rack and Westbury, 1969; Stevens, 1996). The order of the $\omega_{drive}$ conditions was randomized to counteract fatigue effects. Peak forces recorded in each of the 3 contractions were averaged and normalized to the peak force from the 100 Hz condition.

2.4. Environment and exoskeleton parameter selection

We selected motor controller parameters to maintain the same system resonant frequency ($\omega_{res}$) across conditions and preparations. System resonant frequency was assumed to adhere to the following equation:

$$\omega_{res} = \frac{\omega_{drive}}{\sqrt{1 - \omega_{drive}^2}}$$

where $\omega_{drive}$ is the effective passive MTU stiffness, $M$ is system mass, and $\omega_{drive}$ is MTU input and mass output moment arms, respectively (Fig. 1A). To initially determine $\omega_{res}$ and $k_{MTU}$ for each experimental preparation, the MTU was allowed to oscillate passively against a simulated inertial/gravitational load previously used in similar experiments (Robertson and Sawicki, 2015) ($L = 1 - L_{c} = 21$ $M =$ 0.085 kg) (Fig. 1C).

Once $k_{MTU}$ was determined, $\omega_{res}$ and $M$ were varied to approximate $\omega_{res} =$ 2 Hz for each preparation (Table 1, Fig. 1C). In subsequent dynamic conditions, simulated exoskeleton spring stiffness was set as a percentage of measured $k_{MTU}$ based on previous modeling results (Robertson et al., 2014). In the aforementioned in silico studies, $k_{MTU}$ was scaled as a percentage of modeled SEE stiffness, which was triple the stiffness of the whole MTU (i.e., $k_{SEE} = 3k_{MTU}$). Because we used measured $k_{MTU}$ values as a guide in the current study, model based predictions were adjusted accordingly (e.g., the $k_{SEE} = 60\% k_{MTU}$ condition here is comparable to the $k_{SEE} = 20\% k_{MTU}$ in previous simulation work) (Robertson et al., 2014).

2.5. Experimental execution

A 300 ms fixed end contraction was performed under an initial passive load (~10 N, based on previous experience) to determine an approximate value of peak isometric force ($F_{max}$) for active muscle. Next, an initial passive pulse was performed, $k_{MTU}$ was determined, and system inertial parameters were adjusted to approximate $\omega_{res} =$ 2 Hz. Then, 3 consecutive fixed end contractions ($\omega_{drive} =$ 2.0 Hz, $T_{d} =$ 50 ms, $\omega_{drive}$ = 100 Hz) were performed to determine a baseline average peak force for a later fatigue assessment.

Following initial identification of system parameters, five combinations of normalized exoskeleton stiffnesses and muscle activation were explored. Three of these combinations were selected based on parameter values from a previous modeling study (Robertson et al., 2014) and were as follows: (1) 100% Stim ($\omega_{drive} =$ 100 Hz), 0$\%$ $k_{MTU}$ ($k_{MTU} =$ 0), (2) 80$\%$ Stim ($\omega_{drive} =$ 60 Hz), 60$\%$ $k_{MTU}$ ($k_{MTU} =$ 60$\%$ $k_{MTU}$), and (3) 60$\%$ Stim ($\omega_{drive} =$ 40 Hz), 120$\%$ $k_{MTU}$ ($k_{MTU} =$ 120$\%$ $k_{MTU}$) (Fig. 1B). The order of these trials was randomized to counteract fatigue effects. Each combination consisted of 10 stimulus pulse trains. The first five allowed the system to reach a steady state, and the last five were used in subsequent analysis (Fig. 1D and E). Each condition began with the mass sitting on a virtual `table` which supported its weight until a target threshold force was reached. In previous experiments (Robertson and Sawicki, 2015), the table force threshold ($F_{table}$) was computed as follows:

$$F_{table} = (I_{ave}/I_{max})Mg$$

where $g$ is gravitational acceleration (9.8 m/s$^2$). In conditions with reduced activation, this constraint was relaxed. Table thresholds for $\omega_{drive} =$ 100 Hz, 60 Hz, and 40 Hz conditions were 100$\%$, 50$\%$, and 25$\%$ of $F_{table}$, respectively.
Following all dynamic experimental conditions, a second set of 3 fixed-end contractions was performed. The average peak force was determined, and if the percentage of peak force achieved in the final set was >50% of that achieved initially, the experiment was considered a success ($\text{Fatigue} = \frac{66.8}{14.5}\%$). Finally, a second passive pluck was performed to measure $x_0$ with modified loading parameters selected to approximate $2\text{ Hz}$. This was performed last to avoid damaging biological tissue under increased loading conditions.

2.6. Experimental metrics

To insure consistent between-preparation comparisons, we normalized all absolute muscle (CE) length values to an estimated $l_0$, CE velocities to an estimated $v_{\text{max}}$, force data to a measured $F_{\text{max}}$, and metabolic and mechanical power metrics were scaled by CE mass (Robertson and Sawicki, 2015). Estimates of metabolic energy consumption were based on normalized muscle velocity and modeled mus-
cule activation level using estimates of activation and deactivation time constants ($\tau_{\text{act}}$ and $\tau_{\text{deact}}$, respectively). Further details of calculations and assumptions used for experimental metrics can be found in Supplementary methods text.

2.7. Statistical analyses

For data that includes all subjects, outcomes over the last five stimulation cycles for each condition and preparation were averaged. These averages were then used as individual data points in statistical analysis to determine reported mean and standard error. We combined muscle activation and exoskeleton stiffness into a single descriptive independent variable called the “compensation index” (CI) computed as follows:

$$CI = (100 - \%\text{Stim}) + \%k_{\text{MTU}}$$

Table 2

| Table 2 | Mean ± 1 SD values of measured and predicted physiological constants from all experimental subjects. |

<table>
<thead>
<tr>
<th>Physiological parameter</th>
<th>Mean ± STD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial $c_0$</td>
<td>2.40 ± 0.11 Hz</td>
</tr>
<tr>
<td>Initial $k_{\text{MTU}}$</td>
<td>8559 ± 919 N/m</td>
</tr>
<tr>
<td>Adjusted $k_{\text{MTU}}$</td>
<td>23.6 ± 0.89</td>
</tr>
<tr>
<td>Adjusted $M$</td>
<td>0.095 ± 0.004 kg</td>
</tr>
<tr>
<td>Adjusted $c_0$</td>
<td>2.25 ± 0.05 Hz</td>
</tr>
<tr>
<td>Final $k_{\text{MTU}}$</td>
<td>11,241 ± 681 N/m</td>
</tr>
<tr>
<td>$F_{\text{max}}$</td>
<td>42.00 ± 9.63 N</td>
</tr>
<tr>
<td>$\tau_{\text{act}}$</td>
<td>0.074 ± 0.006 s</td>
</tr>
<tr>
<td>$\tau_{\text{deact}}$</td>
<td>0.100 ± 0.002 s</td>
</tr>
<tr>
<td>$k_{\text{MTU}}$</td>
<td>14.57 ± 1.23 mm</td>
</tr>
<tr>
<td>$v_{\text{max}}$</td>
<td>–201 ± 17.03 mm/s</td>
</tr>
<tr>
<td>Muscle mass</td>
<td>5.52 ± 1.17 g</td>
</tr>
<tr>
<td>Animal mass</td>
<td>406.6 ± 42.6 g</td>
</tr>
<tr>
<td>Fatigue %</td>
<td>66.8 ± 14.5%</td>
</tr>
</tbody>
</table>

3. Results

3.1. Pulsed rate coding and activation/force modulation

Based on outcomes from this small study of fixed end contractions in the absence of series tendon, we determined that activation levels of 100%, 80%, and 60% could be reliably achieved for $\omega_{\text{spike}}$ values of 100 Hz, 60 Hz, and 40 Hz, respectively ($p < 0.0001$, $R^2 = 0.86$) (Fig. 1B, Table 1).

3.2. Work loop dynamics

For parameter combinations selected to mimic human neuromechanical response to an external device, MTU and/or MTU + Exo stiffness was generally constant and net work was ~0 in all conditions (Fig. 2Ai).

3.3. System dynamics vs. time

All experimental conditions shown here resulted in symmetric and alternating phases of lengthening/negative power and shortening/positive power (Fig. 2B–F). Within-subject standard devia-

Please cite this article in press as: Robertson, B.D., et al. A benchtop biorobotic platform for in vitro observation of muscle-tendon dynamics with parallel mechanical assistance from an elastic exoskeleton. J. Biomech. (2017), http://dx.doi.org/10.1016/j.jbiomech.2017.03.009
tions in force, length, and power vs. time were relatively low, and mechanical behavior was generally cyclic.

3.4. Peak force and phasing

For conditions meant to reflect human neuromechanical response to Exo assistance, MTU force decreased significantly \( (p = 0.0015, R^2 = 0.55) \) in agreement with H1, while Exo and MTU + Exo increased significantly \( (p < 0.0001, R^2 = 0.86 \) and \( p = 0.035, R^2 = 0.43 \), respectively) with increasing \( k_{\text{Exo}} \) and decreasing \( \phi_{\text{spike}} \) (Fig. 3A, Table 2).

The phasing of peak force was consistent across all conditions, and occurred at almost exactly 50% of a cycle (Fig. 3B). The phasing of stimulation onset, however, varied significantly \( (p = 0.034, R^2 = 0.43) \) for conditions meant to be reflective of human behavior; and increased from \( \sim 30\% \) in the \( (100 \text{ Hz}, 0\% k_{\text{MTU}}) \) condition, to \( \sim 50\% \) in the \( (40 \text{ Hz}, 120\% k_{\text{MTU}}) \) condition (Fig. 3B, Table 2).

Fig. 2. (A) Representative mean work loops for biological components in the (i) \( (100 \text{ Hz}, 0\% k_{\text{MTU}}) \), (ii) \( (60 \text{ Hz}, 60\% k_{\text{MTU}}) \), and (iii) \( (40 \text{ Hz}, 120\% k_{\text{MTU}}) \) conditions, as well as (iv) MTU + Exo work loops for all three conditions. Note that while biological stiffness changes across conditions (i–iii), MTU + Exo (iv) does not. Representative time series data over 4 cycles ± 1 SE of (B) force, (C) length, and (D) power versus time for the (i) \( (100 \text{ Hz}, 0\% k_{\text{MTU}}) \), (ii) \( (60 \text{ Hz}, 60\% k_{\text{MTU}}) \), and (iii) \( (40 \text{ Hz}, 120\% k_{\text{MTU}}) \) conditions. Note that biological excursions increase, force/power is shared between MTU and Exo components, and variation from cycle to cycle is generally small.
3.5. Muscle mechanical state

Significant trends were observed in muscle (CE) strain at peak force (Fig. 4A). No significant trends were observed in muscle (CE) velocity at the time of peak force (Fig. 3D, Table 2), but there were significant increases in peak shortening velocity within a stimulation cycle, in agreement with H2 ($p = 0.04, R^2 = 0.42$) (Fig. 3E, Table 2).

3.6. Power output dynamics

For all conditions examined here, MTU + Exo $P_{\text{mech}}$ $\approx$ 0, indicating mechanical behavior that was cyclic and steady (Fig. 5A). Significant increases in MTU + Exo $P_{\text{mech}}$ ($p = 0.046, R^2 = 0.27$) (Fig. 5A) occurred concomitantly with significant decreases in MTU $P_{\text{mech}}$ ($p = 0.013, R^2 = 0.39$) and $P_{\text{mech}}$ ($p = 0.0017, R^2 = 0.55$) (Fig. 5B) (Table 2). We also observed significant decreases in the magnitude of CE $P_{\text{mech}}$ ($p = 0.025, R^2 = 0.33$) (Fig. 5C), SEE $P_{\text{mech}}$ ($p = 0.031, R^2 = 0.31$) (Fig. 5D), and, in agreement with H3, near constant CE $P_{\text{mech}}$ in these conditions (Fig. 5D) (Table 2). This all coincided with significant increases in Exo $P_{\text{mech}}$ ($p = 0.0008, R^2 = 0.70$) and Exo $P_{\text{mech}}$ ($p = 0.0003, R^2 = 0.74$) (Fig. 5E, Table 2). When MTU power production was broken down into percent contribution from CE/SEE and Exo (where appropriate), there were significant decreases in both %CE ($p = 0.001, R^2 = 0.68$) and %SEE ($p < 0.0001, R^2 = 0.81$) $P_{\text{mech}}$ occurring concomitantly with significant increases in %Exo $P_{\text{mech}}$ ($p < 0.0001, R^2 = 0.91$) (Fig. 5F, Table 2).

3.7. MTU and MTU + Exo stiffness

Changes in MTU + Exo stiffness were non-significant across all conditions ($p = 0.10, R^2 = 0.19$), but MTU stiffness dropped significantly as exoskeleton stiffness increased ($p < 0.0001, R^2 = 0.81$) (Table 2, Fig. 3C), in agreement with H4.

3.8. Modeled metabolic cost and apparent efficiency, $\kappa_{\text{app}}$

For human-like combinations of $\omega_{\text{spike}}$ and $k_{\text{Exo}}$ we observed decreased estimated metabolic demand (Fig. 6A), increased MTU + Exo $\kappa_{\text{app}}$ (Fig. 5B), decreased MTU $\kappa_{\text{app}}$ (Fig. 6C), and a relatively constant CE $\kappa_{\text{app}}$ (Fig. 6D). The only significant trend was MTU + Exo $\kappa_{\text{app}}$ ($p = 0.024, R^2 = 0.46$) (Table 2).

4. Discussion

Using previous modeling and experimental outcomes as a guide (Robertson et al., 2014; Robertson and Sawicki, 2014, 2015) we developed a benchtop biorobotic platform for directly observing muscle-level effects of parallel mechanical assistance from a passive elastic exoskeleton. We hypothesized and observed that combinations of reduced muscle (CE) activation ($\omega_{\text{spike}}$) and increased exoskeleton (Exo) stiffness ($k_{\text{Exo}}$) exhibiting human-like behavior in modeling studies (Robertson et al., 2014) would result in (H1) reduced muscle-tendon unit (MTU) forces (Figs. 2 and 3A), (H2) increased muscle peak shortening velocities (Figs. 2 and 4B–C), (H3) constant muscle average positive mechanical power output, $P_{\text{mech}}$ (Figs. 2 and 5C) and (H4) constant estimated metabolic demand ($\kappa_{\text{app}}$) (Fig. 6A).
system (MTU + Exo) stiffness ($k_{MTU+Exo}$) (Fig. 3C). These in vitro results aligned well with experimental outcomes from human experiments, establishing for the first time that neuromuscular adaptation to an assistive device can be replicated using a bench-top biorobotic platform.

Using our biorobotic testbed, we programmed an in silico parallel elastic exoskeleton (Exo) to deliver virtual forces that replaced a substantial portion of the biological MTU force observed in the unassisted condition (100 Hz, 0\% $k_{MTU}$) (Fig. 3A). Peak MTU + Exo forces increased with decreasing $\delta_{\text{stim}}$ and increasing $k_{Exo}$, but the MTU experienced reduced loading (Fig. 3A). This, in turn, necessitated reduced tendon strains (i.e., absolute lengths), and increased tendon excursions due to a shift in operating point onto the nonlinear (and more compliant) ‘toe’ region (Fig. 2aii-iii).

Reduced forces alone, however, did not guarantee the observed increases in muscle (CE) excursion that resulted in constant CE $P_{\text{mech}}$. This behavior emerged due to decreased strain and increased compliance of the tendinous tissues (SEE) (Fig. 2Ai-iii, C) which increased CE shortening velocity (Fig. 4C) and reduced CE strain (Fig. 4A). Some combination of muscle activation dynamics, muscle force-length-velocity operating point, history dependent CE and SEE properties, and Exo dynamics drove this outcome; although it is not possible to identify how these factors contributed individually.
4.1. Exoskeletons impart performance benefits despite a ‘de-tuned’ neuromechanical system

Previous studies have demonstrated that, during bouncing gait, biological muscle-tendon (CE-SEE) interaction is ‘tuned’, with CEs generating high forces to remain strut-like and cycle energy in SEE’s (Farris et al., 2013; Lichtwark and Wilson, 2005; Roberts and Azizi, 2011; Takeshita et al., 2006). By manipulating levels of CE activation ($\omega_{\text{drive}}$) and exoskeleton (Exo) assistance $k_{\text{Exo}}$ ($\%k_{\text{MTU}}$), we demonstrated that benefit can be derived from a ‘de-tuned’ biological system in the form of reduced biological force (Figs. 2A-B and 3A), CE strains (Fig. 4A), and estimated metabolic cost (Fig. 6A) as well as increased MTU + Exo apparent efficiency, $\varepsilon_{\text{app}}$ (Fig. 6B). The only non-ideal outcome we found evidence for was decreased biological MTU $\varepsilon_{\text{app}}$, although trends were not significant (Fig. 6C). All of these observations are in line with those from human studies (Chang et al., 2008; Farris et al., 2013; Grabowski and Herr, 2009; Kao et al., 2010), except absolute CE strain, which increased in modeling studies (Robertson et al., 2014), and remained constant in human experiments of spring-loaded hopping (Farris et al., 2013).

4.2. Exoskeletons can modulate the frequency-phase coupling relationship that determines muscle-tendon (MTU) ‘tuning’

Studies of human-exoskeleton interaction have demonstrated that some assistance can be metabolically advantageous, while too much can be detrimental (Collins et al., 2015; Grabowski and Herr, 2009). Others have shown that frequency of movement also influences where metabolic benefit is derived in spring-assisted hopping (Farris and Sawicki, 2012). Modeling studies have identified a terminal device stiffness, beyond which muscle activation must be increased rather than decreased to meet performance criteria (Robertson et al., 2014). While these studies collectively identify factors limiting benefits of lower-limb passive exoskeletons, they do not reveal the mechanisms underlying these emergent behaviors.

Our benchtop biorobotic approach provides some further insights into the mechanistic underpinnings of human-exoskeleton interaction. In a recent study probing neuromechanical control of resonant or ‘tuned’ MTU dynamics without exoskeleton assistance, we found that stimulating a biological MTU with feed-forward drive ($\omega_{\text{drive}}$) matched to the system passive oscillation frequency ($\omega_0$) resulted in highly tuned CE-SEE interactions. We also found that shifting $\omega_{\text{drive}}$ too far from $\omega_0$ de-tuned the system, and significantly diminished energy storage/return in the SEE (Robertson and Sawicki, 2015). In the current study, we observed a comparable trend by altering $\omega_0$ via increasing $k_{\text{Exo}}$ with a constant $\omega_{\text{drive}}$ (Figs. 2, 3B and 5F). The effect, however, was the same. That is, a $\omega_{\text{drive}}$ misaligned to the system $\omega_0$ resulted in de-tuned MTU mechanics.

Our benchtop studies suggest that there is a fundamental frequency-phase coupling relationship that ultimately determines whether muscle (CE) activation timing is suitable for elastic energy cycling in tendinous tissues (SEE). Furthermore, this frequency-phase coupling depends not only on passive stiffness of the involved biological tissues, but also the dynamics of the environment, both of which are influenced by the addition of exoskeleton assistance. These findings agree with previous studies of frequency-phase coupling during human bouncing (Merritt et al., 2012). Merritt et al. showed that people prefer metabolically optimal movement frequencies during ankle-driven bouncing (Merritt et al., 2012). A follow-up study demonstrated that this preferred frequency of movement exhibited hallmarks of mechanical resonance.

**Fig. 6.** Plots of mean ± 1 SD for (A) average metabolic rate, (B) total apparent efficiency, (C) MTU apparent efficiency, and (D) CE apparent efficiency. Note that only trends on overall system efficiency (i.e. MTU + Exo) are statistically significant.

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conditions such as spinal cord injury, stroke, and healthy aging result in observable gait pathologies that are accompanied by changes in material properties (i.e., stiffness, k in Eq. (1)) of both muscle and tendon (Franz and Thelen, 2016; Maganaris et al., 2006; Magnusson et al., 2008; Zhao et al., 2009). It is also well documented that these clinical populations have altered neural reflex, which may limit their ability to identify new resonant movement frequencies due to structural changes in biological tissues. Findings from this study suggest that, especially for individuals with reduced ability to adapt novel coordination patterns via reflex (Raburn et al., 2011). Raburn et al. also observed that humans could identify new resonant frequencies after environment dynamics were altered by introducing stiffness or mass in parallel with the body; and that reflexes were necessary for rediscovering $\omega_0$ (Raburn et al., 2011). This and previous studies collectively suggest that resonant movement frequencies for ankle-dominated tasks can be described simply by the relationship shown in Eq. (1), and that reflexive feedback is required for adaptation in novel mechanical environments (Merritt et al., 2012; Robertson and Sawicki, 2015).

4.3. Resonance as a guiding principle for ‘re-tuning’ neuromechanical function

Conditions like spinal cord injury, stroke, and healthy aging result in observable gait pathologies that are accompanied by changes in material properties (i.e., stiffness, $k$ in Eq. (1)) of both muscle and tendon (Franz and Thelen, 2016; Maganaris et al., 2006; Magnusson et al., 2008; Zhao et al., 2009). It is also well documented that these clinical populations have altered neural reflex, which may limit their ability to identify new resonant movement frequencies due to structural changes in biological tissues. Findings from this study suggest that, especially for individuals with reduced ability to adapt novel coordination patterns via reflex (Raburn et al., 2011). Raburn et al. also observed that humans could identify new resonant frequencies after environment dynamics were altered by introducing stiffness or mass in parallel with the body; and that reflexes were necessary for rediscovering $\omega_0$ (Raburn et al., 2011). This and previous studies collectively suggest that resonant movement frequencies for ankle-dominated tasks can be described simply by the relationship shown in Eq. (1), and that reflexive feedback is required for adaptation in novel mechanical environments (Merritt et al., 2012; Robertson and Sawicki, 2015).

5. Future directions

We hope to test predictions from this study in humans during spring-assisted hopping across a range of stiffnesses applied at the ankle joint. If modeling and in vitro predictions are correct, there should be a ‘goldilocks zone’ in which assistance is not too stiff or too compliant, but just right. At the ideal exoskeleton stiffness, we would expect minimized muscle activity, minimized metabolic demand, constant system (i.e., biological ankle + exoskeleton) stiffness, and constant average positive power in the major plantar flexors (i.e., soleus, medial and lateral gastrocnemius). On the other hand, it is possible that at the highest exoskeleton stiffness settings, users could maintain their baseline neuromechanics and use the device to increase mechanical power output beyond normal physiological levels.

The benchtop biorobotic tested we have demonstrated here is a powerful new tool that can be applied to explore the impact of environment dynamics on the mechanics and energetics of biological muscle-tendon unit (MTU) function. In future work, we hope to begin addressing how exoskeletons influence neural feedback during rhythmic movement by combining existing tools with instrumentation to record directly from 1a and 1b sensory afferents (i.e., muscle spindles and golgi tendons) during simulated assisted and unassisted locomotion. This approach may give important insight into the neural mechanisms underlying adaptation to assistive devices.

Conflict of interest statement

We have no conflicts of interest to report.

Acknowledgements

We would like to thank funding sources, including grants from the UNC/NC State Rehabilitation Engineering Core (REC) and grant number 2011152 from the United States – Israel Binational Science Foundation awarded to GSS.

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jbiomech.2017.03.009.

References


Hocoma.


