Who is Walking Whom? Control Strategies for Exoskeleton-Assisted Walking

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ABSTRACT

Exoskeletons have been shown to effectively assist walking using a variety of control architectures. We categorize high-level exoskeleton controllers into two categories: steady-state and co-adaptive. The former prescribes an assistance pattern for a given amount of time and assesses a biomechanical metric over that period before updating the pattern and reassessing. This technique has been implemented in many successful exoskeleton experiments. Co-adaptive controllers update assistance on a stride-by-stride basis, meaning they require a more rapidly-responding biomechanical signal, but enable an exoskeleton to dynamically adapt with its user and therein expedite the process of optimizing assistance. Because this strategy is promising yet under-studied, we propose a new co-adaptive controller that operates based on a set of heuristics that link the user's biological torque and the exoskeleton torque: generally, if user torque is high at a given percent stride, then exoskeleton torque can be increased and vice versa. This controller builds upon previously conducted work with co-adaptive exoskeleton control, and may offer benefits not available in steady-state controllers, such as expedited training times in high-dimensional problems (e.g. many degree-of-freedom exoskeletons).

OVERVIEW OF CONTROL STRATEGIES FOR LOWER-LIMB EXOSKELETONS

Exoskeletons are mechanical devices that interface with and assist their user's biomechanics. Their applications range from restoring mobility to stroke survivors (Bortole et al. 2015), reducing energetic cost of walking for older adults (Galle et al. 2017) and runners (Nasiri et al. 2018), and enhancing the load-carrying capabilities of soldiers (Yu et al. 2014). In the last decade, walking exoskeletons have become increasingly complex. In 2013, an ankle exoskeleton reported by Malcolm et al. was the first to break the metabolic cost barrier; their device made users 6% more energetically efficient than when they walked with normal shoes. Now, higher dimension hip-knee-ankle devices are realizing even greater success, with the most recent advancement coming from Franks et al. (2021), who report a 50% reduction in the metabolic cost of walking with whole-leg assistance.

A primary reason why the field continues to improve is due to advancements in control strategies. Control strategies are programmed systems that synthesize sensor information and adjust actuators. An efficacious controller can make an exoskeleton more effective at reducing the energetic cost of walking, reduce the time it takes for new users to learn to operate the device, and even enable adaptation of a device to its user. While at a low level, most controllers operate similarly (applying a prescribed torque profile at each joint as a function of percent stride), variations in technique exist to generate the shape of said assistance profile. Many exoskeleton researchers approach this problem from a biomechanical framework, in which assistance is informed by biological measurements such as heart rate, metabolic rate, neural activity, muscle activity, or joint kinetics.

Some biological factors change slowly (heart rate or metabolic rate) and can be noisy (metabolic rate or muscle activity), meaning longer-term measurements are required before a control strategy can be evaluated and updated. Because this period can span multiple strides or even minutes, we refer to this group of control strategies as *steady-state*. Steady-state control may prove beneficial in forcing the user to explore gait patterns unusual but advantageous to them. Still, it can lead users to feel that they do not have influence over the exoskeleton's behavior. This issue is exacerbated with control based on metabolic rate or neural activity because users struggle to accurately assess and consciously regulate these metrics. In contrast, muscle activity and biological joint torque measurements can be acquired quickly and modulated consciously by users, enabling *co-adaptive* control in which prescribed joint torques are updated on a step-by-step basis.

The goal of this report is to assess current high-level control strategies for walking exoskeletons, with a specific objective of illustrating the differences between steady-state and co-adaptive control strategies. After comparing the benefits and drawbacks of each, we identify an untapped control strategy, and propose a study that would utilize this technique to clarify potential advantages of co-adaptive control.

Review of Steady-State Strategies

Control via Metabolic Expenditure. Koller et al. (2016) were among the first to report the development of an optimization strategy that employs physiological measurements in a control optimization loop. They designed a framework to assess and minimize a cost function based on a user's average metabolic measurements over 6 minutes. Using indirect calorimetry, which measures O_2 inspired and CO_2 exhaled and infers metabolic cost using the Brockway equation (Brockway 1987), Koller and colleagues optimized a single parameter (torque onset time) for bilateral ankle exoskeletons and achieved an 18% decrease in metabolic cost of walking.

However, the optimization algorithm employed rapidly becomes more complex with an increasing number of parameters to tune. To circumvent this problem, Zhang et al. (2017) used an evolutionary algorithm which assesses the metabolic costs of one "generation" of multiparameter control laws, picks the best-scoring law, and creates the next generation for assessment using the previous best-scoring law as a starting point. Utilizing indirect calorimetry and an ankle exoskeleton dependent on four control parameters, Zhang and colleagues were able to realize a 24% reduction in metabolic cost of walking. This strategy and others like it (e.g. Bayesian optimization reported by Ding et al. 2018) demonstrate how steady-state metabolic control has become one of the most popular methods for optimizing exoskeleton assistance.

EEG-Based Control. Because motor commands originate from the central nervous system, it is natural to ponder the possibility of using neural signals for exoskeleton control. Kilicarslan et al. (2013) developed a novel electroencephalography (EEG) decoding algorithm to determine a paraplegic user's intentions when walking in an exoskeleton (i.e. walk or stop). In 2017, Liu et al. designed an EEG-controlled exoskeleton to improve gait training for patients with neurological diseases such as spinal cord injury or paralysis. One healthy subject has thus far been able to command the device to step with the left or right leg in a pre-planned trajectory via 1) sensorimotor rhythms generated by users kinesthetically imagining left/right hand motion or 2) movement-related cortical potentials generated by left/right hand motion.

There are few other EEG-controlled exoskeletons, likely because EEG is highly susceptible to noise and movement artifacts, it requires significant focus by the user, electrode caps are difficult to don/doff so transitioning out of the laboratory is less feasible, and the process of using neural signals to infer kinematic goals is more complex than using muscle activity. Surgically implanted electrode arrays could address some of these issues, but the invasive nature of these procedures would detract from the otherwise non-invasive benefits of exoskeletons.

EMG-Based Control. Muscle activity measured non-invasively by electromyography (EMG) is another feasible input for generating assistance profiles. One steady-state example of this technique comes from pilot trial data reported by Zhang et al. (2017). An evolutionary algorithm was used to alter torques such that plantarflexor muscle activity was minimized. The optimizer reduced soleus activation by 41%; however, the assistance profile that did so was notably different from the profile derived using indirect calorimetry. This may indicate that steady-state EMG control is not a preferable surrogate for metabolics control because the EMG-optimized assistance pattern tends to offload activity to muscles not recorded by EMG. This problem could be alleviated in part by acquiring signals from synergistic muscles (e.g. soleus and gastrocnemius).

Review of Co-Adaptive Strategies

EMG-Based Control. While steady-state EMG control has demonstrated some success, there is evidence that controllers which adapt to the user may expedite learning time, simplify optimization strategies, and more rapidly improve metabolic expenditure. Koller et al. (2015) developed a bilateral ankle exoskeleton controller with an adaptive gain that updated each stride according to the peak soleus EMG from the previous stride. They demonstrated that a maximum metabolic cost reduction of 18% could be achieved in just one 50-minute session, while an EMG-based controller with a fixed gain required three days of training to achieve the same reduction (Sawicki and Ferris, 2008).

Jackson and Collins (2019) also sought to develop an adaptive EMG controller, but one that uses a heuristic approach to capture human-exoskeleton interaction. They assumed that muscle activity in cooperation with an exoskeleton torque (e.g. soleus activity during plantarflexion) indicates that user desires and would benefit from more torque, and that muscle activity in opposition to the exoskeleton (e.g. tibialis anterior activity during plantarflexion) indicates the user wants less torque. After 30 minutes of heuristic optimization, Jackson and Collins reported an average metabolic cost reduction of 22% relative to the powered-off condition. The efficacy of this method is especially promising for higher-dimension exoskeletons, given that traditional optimization algorithms become exponentially more time-consuming as parameters are added.

Biological Joint Torque-Based Control. Prevalent theory suggests that humans adapt to walking with exoskeletons such that the net (human plus device) moment is invariant with that of unassisted walking (Lewis and Ferris, 2011). Thus, biological joint moments are an important metric for intuiting the human response to exoskeletons and a potentially powerful controller input. Researchers have recently begun to explore real-time methods of estimating biological joint torques without biomechanical tools such as motion capture that are often infeasible to integrate bulky devices.

Liang and Hsiao (2020) proposed a whole-leg dynamical model to determine the human response to a hip-knee exoskeleton using exclusively on-board measurements. The model relates exoskeleton joint angles and motor currents to exoskeleton and biological torques. While the theory is a promising step toward real-time torque-based control, experimental verification was rudimentary and testing was not conducted on full walking experiments.

To bypass complex modeling, Gasparri et al. (2019) proposed a sensor-based method of estimating biological ankle moment. Assuming a perfect equilibrium between ground reaction forces and the torque produced by ankle muscles, a polynomial regression was used to directly map foot sensor force to biological moment. The prescribed exoskeleton torque for each step was a proportionally scaled fraction of the estimated moment. This technique was effective at reducing metabolic cost of transport by 17-27% across participants with cerebral palsy, Parkinson's, and no motor impairment. While this technique has impressive clinical implications, it does not scale well to multi-joint assistance. Further, the proportional scaling does not allow the exoskeleton to augment walking when the ankle is not doing work. Greater improvements may be observed if the exoskeleton torque can vary from that of the ankle.

Conclusions from Review. While a wide variety of exoskeleton controllers have already been reported, gaps in current knowledge specifically related to co-adaptive control remain. Few published exoskeleton studies utilize co-adaptive controllers, and even fewer attempt to compare co-adaptive controllers to their steady-state counterparts. This makes it difficult to understand the differences in efficacy and in appropriate applications of these two controller variants. Co-adaptive control has also only been tested in single-joint exoskeletons, meaning its strengths in efficiently solving high-dimensional problems is unexplored. We posit that biological moment is a promising input for co-adaptive control, and may be just as advantageous as the EMG-based control demonstrated by Jackson and Collins (2019), while providing the additional benefit of a cleaner and more consistent control signal, which may enable faster exoskeleton optimization.

RESEARCH PROPOSAL

Project Overview. Though proven to effectively reduce metabolic rate, steady-state controllers require extensive optimization times. In Franks et al. (2021), three participants walked for 50, 73.5, and 135 hours respectively in order to optimize assistance with a hip-knee-ankle exoskeleton.

Walking for such long durations may be infeasible for older adults, clinical populations, and studies that require larger sample sizes. With a faster-iterating control strategy, the search space of potential assistance profiles can be explored more rapidly, hopefully reaching an optimal metabolic reduction and completing training in less time, thereby reducing user burden. While Jackson and Collins (2019) demonstrated that heuristic-based control can achieve considerable metabolic reductions (22%) in just 30 minutes, this strategy has not yet been tested on multi-joint assistance. Thus it is unknown if such a strategy could produce the same extreme metabolic reductions (50%) as observed in the longer optimization protocol used by Franks et al. (2021).

We hypothesize that using a biological torque-based heuristic controller will enable a faster decrease in metabolic cost of walking in the Bilateral Lower Limb Exoskeleton (BiLLEE; Bryan et al. 2020),. The proposed co-adaptive heuristics, applicable at any given point in stride, are: 1) If biological torque is larger than exoskeleton torque and both are acting cooperatively, increase exoskeleton torque magnitude. 2) If the exoskeleton and user are acting antagonistically, decrease exoskeleton torque magnitude. 3) If the exoskeleton torque is greater than or equal to biological torque, and both are acting in the same direction, do not change exoskeleton torque.

We propose the use of biological joint torques as an input modality for three main reasons: 1) It does not require additional hardware to be used in conjunction with BiLLEE. Past experiments have shown that physical interference between BiLLEE and EMG electrodes pose a significant challenge to acquiring a usable signal. Indirect calorimetry is also expensive and restricts the use of the system to a laboratory or clinical setting. Our alternative could be a step toward exoskeleton optimization in free living. 2) We are interested in long-term applications of exoskeleton assistance for people with motor impairments and recognize that spastic gait can complicate EMG-based control (Gasparri et al., 2020). 3) We believe that this strategy will provide the user greater comfort and perceived agency while walking. This belief is informed by theory that motor learning prioritizes system-invariant moment patterns and that joint torque is a relatively intuitive metric for users to understand and modulate (Lewis and Ferris, 2011).

Our novel controller will be tested on the experimental setup used in Franks et al. (2021) with the goal of achieving similar metabolic improvements in significantly less time. The provided hardware consists of an instrumented treadmill and BiLLEE, which is equipped with rotary encoders at each joint, load cells at the hips and knees, and strain gauges at the ankles (Figure 1). To calculate biological torques, we will employ real-time inverse dynamics using the ground reaction forces from the treadmill, joint angles from the encoders, and exoskeleton forces and torques from the load cells and strain gauges, respectively (Figure 2.1).

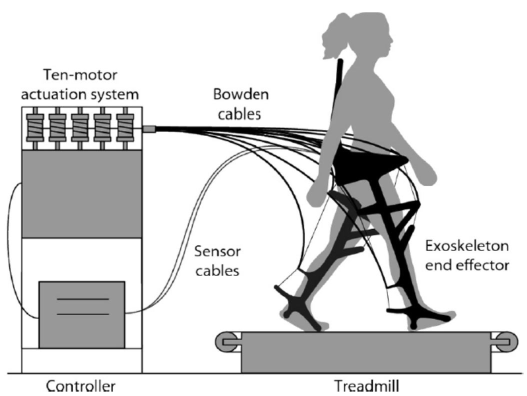

Figure 1. Schematic of hardware system (Bryan et al. 2020).The ten-motor stand actuates hip flexion/extension, knee flexion/extension, and ankle plantarflexion via Bowden cable transmissions.

The acquired biological torque will be sampled throughout the stride at key points particular to the given joint (Figure 2.2) and compared to the exoskeleton torque in that instance (Figure 2.3). The difference between the exoskeleton and biological torques (δ_n) will be calculated, and a change in torque ($\delta\tau_n$) will be determined by the product of δ_n and a scaling factor (k_n; Figure 2.4). The current torque profile will be updated by $\delta\tau_n$ and applied to the exoskeleton in the next stride (Figure 2.5), before the process repeats.

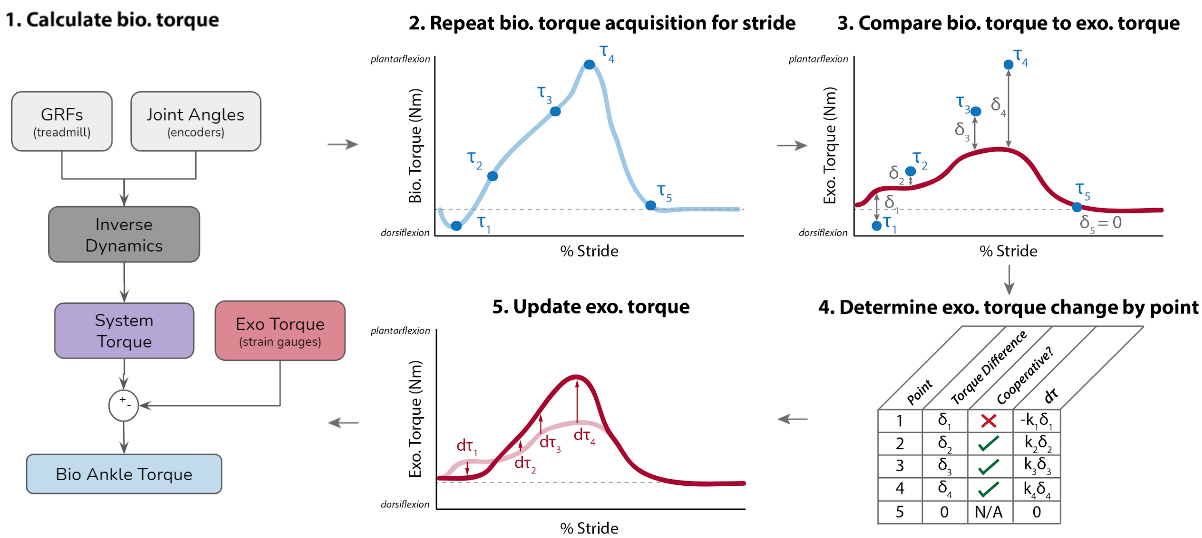

Figure 2. High-level exoskeleton control strategy using a biological torque based heuristic.

Experimental Protocol. We plan to conduct a pilot test to determine the viability of our controller on ankle assistance for one expert user. The subject will train following the protocol outlined in Franks et al. (2021) to enable a broad assessment of the relationship between metabolic reduction and training time. The experiment (n = 5, expert users) will vary stopping time for each participant during hip-knee-ankle assistance. Training will end when the subject either reaches a similar (± 5%) metabolic reduction to Franks et al. (2021) or has walked for the maximum allowable time.

During the experiment, indirect calorimetry will be used to calculate the metabolic rate. A baseline rate will be taken when subjects stand with minimal movement (Quiet Standing; QS). This value will be subtracted from the reported rates during assisted walking (Heuristic Assistance; HA) and unassisted walking (Zero Impedance; ZI) while wearing the exoskeleton. We will normalize HA metabolics to ZI to factor out the effect of BiLLEE's weight and isolate the addition of our controller.

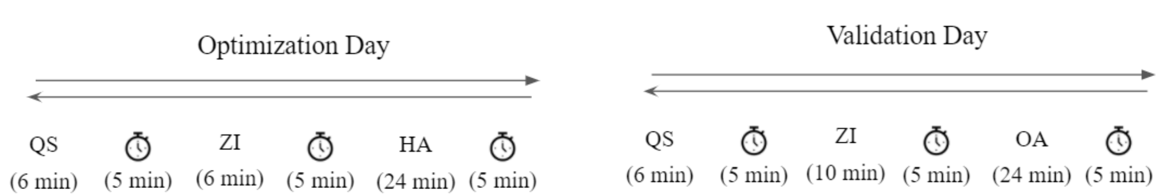

Figure 3. Trial order and lengths for optimization and validation days. Arrows indicate double reversal order (QS-ZI-GA-GA-ZI-QS). Stopwatch symbol indicates a break.

If optimization is not concluded early by achieving the target metabolic reduction, participants will undergo 3 days of torque optimization. On the final day of experimentation, we will apply the heuristic-determined optimal torque profile (OA) over a longer period of time and use indirect calorimetry to assess the assistance's efficacy. The outlined protocol mirrors the methodology used in Franks et al. (2021) and will therein allow for more direct comparison of metabolic cost reduction results. To conclude our experiment, we will add a user feedback session aimed to qualitatively deduce differences in experiencing our controller and BiLLEE's steady-state alternative.

Expected Outcomes and Difficulties. From these efforts, we expect to observe that: 1) Metabolic rate achieves a similar reduction to the steady-state alternative, but stabilizes to this value in less training time. 2) Biological torque decreases and exoskeleton torque increases as the users learn to more effectively supplement their own efforts with that of the exoskeleton. 3) Users state a preference for co-adaptive control due to increased comfort and agency.

A key challenge and consideration in this project will be ensuring user safety and comfort. While many safety systems are already in place for BiLLEE, we recognize that tuning controller gains is difficult and, if done improperly, can force our user to uncomfortable patterns. We may need to explore incorporating and configuring delays between the measured and applied torques or add another stabilizing term to account for neuromuscular delays as in Jackson and Collins (2019). Even in hardware alone, BiLLEE will require continuous maintenance to uphold the comfort of our subjects. The transmission ropes responsible for torque application are frequently compromised due to friction and thus must be closely monitored during experiments.

CONCLUSION

This article sought to profile the differences between co-adaptive and steady-state control. Steady-state control utilizes signals that are often noisy, such as indirect calorimetry, which offer an excellent window into the biology of the user at the cost of requiring much longer optimization times. This strategy is widely used and is responsible for many of the best walking exoskeleton assistance strategies to date. Co-adaptive control, which employs a more consistent signal such as EMG or human kinetics, offers the possibility of an exoskeleton controller that changes with its user. While this strategy is less frequently utilized, it may simplify and speed the optimization process, as well as offer more intuitive control for new exoskeleton users. We propose a new co-adaptive controller that is founded on a biological torque-based heuristic. This controller can be rapidly tested and iterated on using existing hardware in the Stanford Biomechatronics Lab, and its utility may be justified by comparing outcomes to the lab's previously-conducted studies using steady-state control. Future work beyond the scope of our proposed project could focus on understanding the naive exoskeleton user's experience of learning to walk in a steady-state versus co-adaptive controller, which would help clarify how the type of controller impacts user adaptation.

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The 6-minute presentation based on this project is viewable at: ***youtu.be/UvZAP3gCvHU****.*

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