Autonomous vs Direct User Preference in the Control of a Knee Exoskeleton

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***Abstract*—A key barrier to the widespread adoption of assistive exoskeletons is limited user agency in their control. Many assistive lower-limb exoskeletons (ALLEs) largely rely on autonomous control algorithms intended to mimic biologically optimal walking torque profiles. However, this biomimetic walking torque may not accurately reflect the user's true preferences. This work makes three primary contributions: (1) a comparative evaluation of personalized user-generated torque profiles and biomimetic torque profiles, (2) an investigation into user preference between direct user control and autonomous torque delivery, and (3) the development of a novel gait state representation enabling more flexible and robust real-time gait tracking. Real-time gait phase estimation is accomplished using an Extended Kalman Filter (EKF). Output torque is delivered to the user's knee via a lookup table of either biomimetic or user-generated torque profiles based on the percent of the gait phase estimated via an EKF. During the study, participants walk using direct control, the autonomously controlled biomimetic profile, and the autonomously controlled direct user profile. Finally, the user compares the given choices, selecting their preferred method and torque scheme. This study is conducted with three participants to determine whether the chosen model for the autonomous control system is robust enough for use in a larger trial with more participants.**

***Keywords*—exoskeletons, human-robot interaction, assistive robotics, Extended Kalman Filter, control, biomechanics, human-factors**

I. Introduction

Assistive lower-limb exoskeletons offer many ways to improve human lives, from medical mobility aids to enabling greater levels of recreation. Many exoskeleton researchers share the long-term goal of creating devices that achieve widespread adoption, to potentially meaningfully impact daily life. In particular, backdrivable Assistive Lower-Limb Exoskeletons (ALLEs) enhance human locomotion by reducing the work required to walk. For knee exoskeletons, this is typically accomplished through actuators that apply torque at the joint, assisting extension and flexion at appropriate phases of the gait cycle. The total joint torque required for motion is unchanged, and the additional torque reduces the user's metabolic cost. However, despite these benefits, effective human interaction with exoskeletons remains a challenge. Current control strategies—ranging from optimization-based "Body-in-the-Loop" approaches that minimize energetic cost via feedback [1], to direct user input methods that allow users to command joint motion explicitly [2]— present trade-offs in usability, personalization, and performance. Autonomous controllers can enable seamless assistance and reduced metabolic effort, but often fail to incorporate individual preferences and are rarely evaluated directly against user-driven approaches, leaving uncertainty about what users desire. This gap is critical, as a lack of agency can translate to a perceived loss of control, ultimately reducing trust in the device. Such distrust is likely a key factor limiting the widespread adoption of assistive knee exoskeletons [3]. Therefore, establishing control strategies that emphasize user agency, personalization, and intuitive interaction are essential for improving user trust and enabling scalable, real-world deployment of lower-limb exoskeleton technologies.

Creating a control scheme to optimize the subject's metabolic cost is one approach to applying assistive torque while directly considering physiological needs [4]. This approach works by parameterizing a torque profile and optimizing the parameters very slowly while the user walks with the powered device. The robot adapts to optimize performance while the human adapts to the robot. Real-time estimates of a user's biological joint moments are also a potential target of optimization, and resulting iterative, autonomous control approaches have enabled adaptable assistance across gait modes [5]. However, despite metabolically optimized torque profiles being similar across users and highly scalable, they assume that the human walking pattern is solely optimized for metabolic efficiency. The human body prioritizes a combination of variables when determining torque (idiosyncrasies, habit, balance, terrain, etc.), resulting in a pattern that does not always prioritize metabolic efficiency [6]. When unhindered human gaits adapt to atypical terrain, users adopt a similar symmetrical pattern to normal walking, though it is not metabolically efficient. This implies that the human nervous system settles on patterns that balance multiple priorities and sometimes accepts a higher metabolic cost for one that better fits the composite need. There is a distinction between metabolically efficient and biomimetic torque profiles, and metabolically efficient, in particular, does not provide the perceivable change to the user required for

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adoption or the subconscious balance that the human nervous system applies when determining gait patterns [7].

Biomimetic torque application is a control strategy that seeks to replicate the typical human walking pattern. Unlike the previously explored metabolic-efficiency-based approaches, this type of control focuses on leveraging the benefits of the human's natural walking pattern by mimicking it in the exoskeleton's torque profiles. This kind of control assumes a generalized average gait cycle applicable to any human, based on the user's size and terrain. It then imposes this torque on the user, via the chosen mode of control (AI - Artificial Intelligence, TBE - Time Based Estimation, passive control, etc.) [2], [8], [9]. These exoskeletons apply the average cycle to the user, enabling higher accuracy and easier scalability. As these do not require significant tuning between users following initial setup, the exoskeleton can switch users with minimal preparation time. This allows for possible widespread production and applicability to a variety of users. Nevertheless, although these exoskeletons exhibit high scalability potential, personalization is not considered. Users have little agency or input, as their gait is controlled by a generalized algorithm. Personal preferences and individual habits are not taken into account, which could lead to possible dissatisfaction or even distrust in a user. Adoption of assistive exoskeletons relies, in part, on users trusting the technology and finding it sufficiently beneficial to use it [3]. Much of the trust relationship between user and technology is determined by the human-robot interaction [10], particularly in the amount of load control that is shared between the autonomy and the user [11]. For many users, they prefer a level of agency in how their robot (exoskeleton) assists, and a slightly shared level of control tends to increase their trust in the provided automation [12]. Though biomimetic profiles are a reliable, scalable method of control, they do not account for user choice.

Direct user control is an alternative approach for assistive exoskeletons that emphasizes user agency. By giving users full control over their movements, a stronger sense of agency can be established. This is evident in past work, where subjects controlled their movements using AI-camera technology [13]. In another study, a human-in-the-loop approach implemented a biofeedback video game to "maximize learning potential" [14], gamifying the experience while progressively challenging the user and enhancing their sense of control. Similarly, prior work [15] provided subjects with two controllers, each equipped with plungers that allowed them to contract or extend an exoskeleton knee motor. This effectively placed users in direct control of their own assistive gait profile. Under this level of agency, participants produced knee torque profiles that differed significantly from biomimetic patterns, suggesting that user-preferred assistance does not necessarily align with traditionally defined biological ideals. While direct user control offers high personalization and reinforces user agency and trust, it may present challenges in scalability. These benefits are often offset by increased training time and cognitive load [12]. Users must continuously control their legs through input devices, placing demands on coordination and synchronization, effectively requiring them to perform real-time optimization of their own assistance.

This ultimately leads to the aim of this research: to test what type of control users prefer while carefully balancing cognitive load, agency, and preference. An easy way to validate this is to present the user with the choice. To that end, an accurate model of their gait is needed, along with a choice between two torque profiles. For the former, an Extended Kalman Filter (EKF) was used to track the gait state in real time, which was then used to feed into a typical biological torque profile or a direct-user torque gait. These autonomous control methods would be compared with the subject controlling the exoskeleton directly (which would be done beforehand to train the direct-user torque profile) to determine which would provide the greatest personalization, accuracy, and scalability. In particular, removing the direct control cognitive effort burden levels the playing field of comparison, and allows users to assess the preference of their torque profile with greater confidence. Alternative comparison methods [16] primarily focus on metabolic and biomimetic control using impedance strategies and do not consider direct user control. In this paper, we compare direct user control with the autonomous application of biomimetic and user-generated torque profiles to evaluate user preference.

II. Methodology

A. Direct User Control

Participants begin the study with a session of direct user control using a pair of handheld controllers. These HIDs (Human Input Devices) are equipped with two plungers intended for the index and middle fingers to trigger as the participant desires. Pressing down on the upper plunger results in a contraction of the knee by the motor, while pressing the lower plunger results in an extension by the motor. A compression spring provides restoring force to the plunger, and a linear encoder measures position, alongside a Raspberry Pi serving as the analog-to-digital converter (ADC). This ensures a larger and smoother range of values when actuating the knee motor. **Figure 1** shows the four buttons and two plungers as previously described.

Fig. 1. HID Controller held by a participant.

The controllers also include mode-switching buttons to facilitate smooth testing. One button enables recording of both real-time motor encoder data and IMU thigh data, while the others determine the control method (direct or autonomous). To ensure complete user safety, these controllers have also been equipped with soft stops in the unlikely scenario they are dropped during the trial. These are built directly into the devices' wrist straps and immediately cease all motor input upon being triggered. A hard E-Stop button has also been placed at the front of the waist, which cuts power to the exoskeleton when pressed.

B. Modeling and Estimating Gait

To create an autonomous control scheme within the assistive knee exoskeleton, two key features needed to be implemented: 1) a reputable and accurate method for recording real-time spatial data, and 2) a real-time gait state estimator. Gyroscopically sensitive IMUs (Inertial Measurement Units) placed on the thigh of each leg were chosen for sensing. In combination with the controller's button-actuation readings, a fiducial, data-driven gait phase could be digitally constructed from the user's exoskeleton-assisted gait. A Bayesian estimation approach via Extended Kalman Filter (EKF) allows for estimation, considering its comparable performance to other linearized estimators at lower computational cost [17]. More specifically, the EKF serves to output a %phase given real-time angular and velocity data.

The autonomous controller for the knee exoskeleton relies on a biomechanical model of gait kinematics to predict the thigh angle θ_t and its angular velocity $\dot{\theta}_t$. This subject-specific gait model will allow us to infer a subject's gait state vector in real time using the EKF. With our state estimate, the exoskeleton will map the gait state to a corresponding torque profile, representing either traditional biomimetic torque or user-generated torque profiles via direct user input.

The gait state vector x consists of a phase variable p, phase rate $\dot{p}$, bias β, and scale factor α. The phase variable ranges from 0 to 1, increasing monotonically across strides and resets at ipsilateral heel strikes (HS); this represents a normalized time variable so that torque may be delivered at the knee according to the walking gait cycle while maintaining robustness across different or potentially changing walking speeds.

A least-squares regression optimization was used to build the gait tracking model, $h(x)$, delivering gait tracking variables relevant to our exoskeleton sensing capabilities. Thus,

$$\Big(\theta_t(t),\ \dot{\theta}_t(t)\Big)^T = h\big(x(t)\big) \tag{1}$$

where θ_t represents thigh angle, and $\dot{\theta}_t$ represents the velocity of the thigh angle for a given leg. The model was generated using IMU data of thigh angle from steady-state walking on the DUCK-E research platform for each subject. This measurement model will allow for an estimation of the gait state x via the EKF.

Our least squares regressor utilized a Fourier series basis, $R(p)$ of order k defined by

$$R(p) = \begin{pmatrix} 1, & \cos(1 \cdot 2\pi p), & \sin(1 \cdot 2\pi p), & \dots, \\ & \cos(k \cdot 2\pi p), & \sin(k \cdot 2\pi p) & \end{pmatrix} \tag{2}$$

with order $k = 3$ whose construction of sinusoids represents the periodic gait cycle. The thigh angle data for this subject-specific regression model was collected on the DUCK-E research platform at steady-state walking of 1.5 mph.

C. Torque Profile Generation

After estimating a person's gait state (0 to 1), this value was matched to a torque profile to output torque at the corresponding moment. **Figure 2** is the biological, normalized version of what this "lookup" does. Visually, by looking at the x-axis and matching it to the y-axis using the parametrized curves, a torque-out (forward or backward) is determined. This can be done accurately and output to the motors nearly instantaneously because the gait-state model exports gait state % prediction in real time. The biomimetic torque profile in **Figure 2** that follows the typical person's extension/flexion torque [18] was used as one of the two possible autonomous modes.

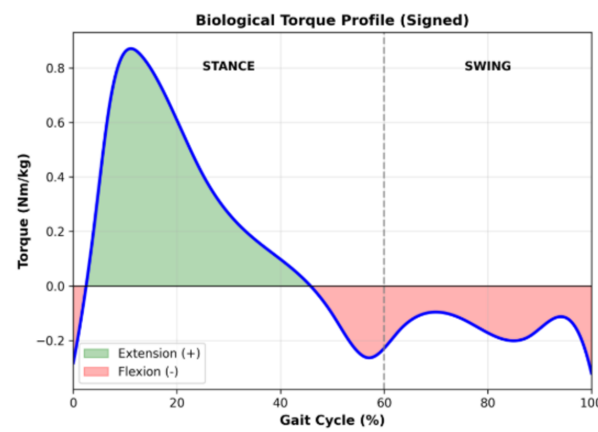

Fig. 2. Typical Biological Knee Torque Profile, Normalized for Matching.

This "lookup" exercise was repeated for the user-based torque profile extracted from a direct control trial. However, before obtaining a well-parameterized curve like that in **Figure 2**, some data processing was required. To segment the data, heel strikes were determined using peak accelerations for each gait cycle and validated with the thigh angles. All torque peaks were detected in this segmented data to produce a "best fit" or average torque profile represented by a weighted average of % gait phase. This procedure was conducted on both knees, resulting in **Figure 4**. This shows the final torque profile for each individual tested and their cumulative average. Finally, in order to better run on the exoskeleton, an individual's profile was further simplified into a spline curve like that shown in **Figure 4**. This resulted in a normalized spline version for simple, computerized matching.

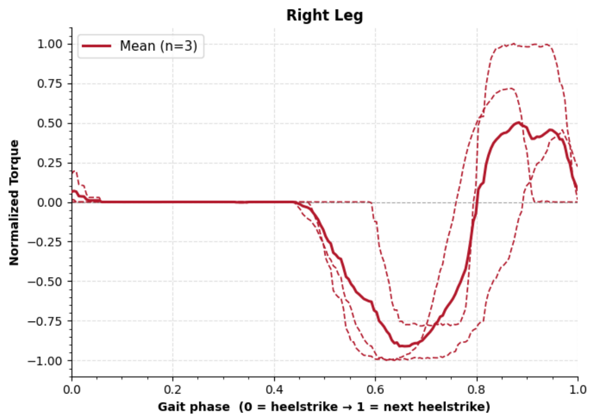

Fig. 3. User Generated Right Leg Torque.

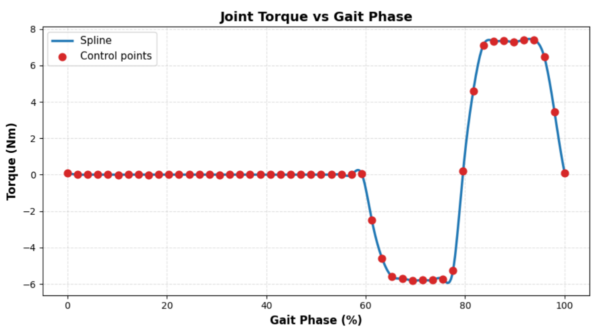

Fig. 4. A Single User's Average Torque Profile Spline.

D. *Human Subject Trial Procedure*

Before beginning human trials, our team conducted extensive work to ensure the safety and well-being of the subjects. Clear instructions for the entire procedure were provided before starting, and preliminary background screenings (e.g., only able-bodied, healthy subjects) were conducted to ensure no safety issues arose. After signing and confirming the procedure, the subjects were ready to move on to the trial.

The trials were divided into three distinct sections. First, the direct user control section, in which the subject was instructed to walk using the hand controllers to alter input torque and walk in accordance with their own best judgment. After a period of getting accustomed to piloting the exoskeleton, data was collected to get an accurate torque profile. Second, an extended Kalman filter (EKF) was used to emulate a typical biological torque profile, which was then exerted on the individual. Third, an EKF was similarly used to simulate the user's personal torque output and predict their subsequent gait phases.

After being briefed on the procedure and the three phases, our team helped the subject into the exoskeleton. Following this process, several checks were conducted to ensure the person's comfort, safety, and the exoskeleton's functionality. Once finished, the three-step physical portion of the exam began. Following the direct control portion, the autonomous portion of the trial was able to proceed, conforming to the person's gait. This can be seen in **Figure 5**. After completing both the direct and the two autonomous control portions of the experiment, the subject was assisted in removing the exoskeleton. Then, a short survey was given to complete, detailing a few key questions about the experience.

Fig. 5. User in Autonomous User Torque Mode.

After initializing the trial, the subjects were prompted to press the direct user control button (no data recording) on the HID. The subjects were then given ample time, both on and off the treadmill, to get accustomed to piloting the exoskeleton. Following this period, the subjects were asked to continue to record their torque inputs in relation to the IMU data. A torque profile could then be created from their data and implemented into the automatic custom torque profile mode. Both autonomous modes were then administered to the subject with the EKF to track the phase throughout. After the three phases, a survey was administered to detail the experience and collect preference feedback. This study protocol was approved by the Texas A&M Institutional Review Board, with IRB ID 2025-1249.

III. Results

A. *EKF tracking for Autonomous Profiles*

The exoskeleton closely tracked and estimated both the joint angles and gait trajectory after tuning the EKF for each participant and their corresponding profile. This joint angle tracking for biological torque profile trials on both the right and left legs is shown in **Figure 6** and **Figure 7**, respectively. Similar tracking results were found within the user torque profile trials. This angle tracking helps verify that the model used to create the EKF is sufficient for estimating walking behavior across participants.

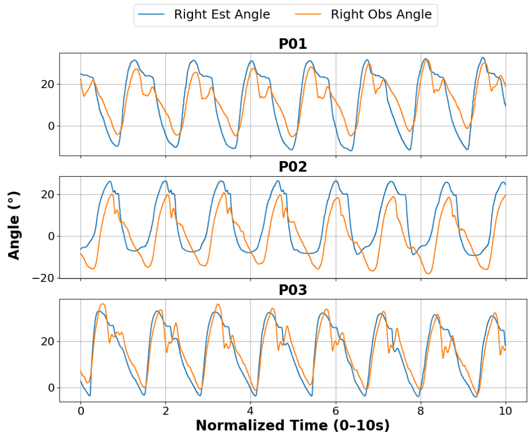

Fig. 6. Estimated and Observed Right Leg Angles vs. Normalized Time.

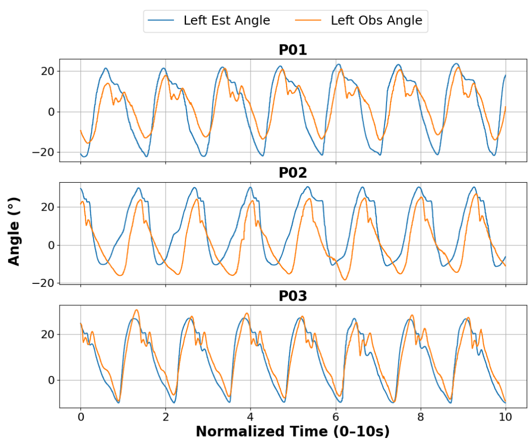

Fig. 7. Estimated and Observed Left Leg Angles vs. Normalized Time.

In addition to these estimated joint angles, the EKF closely tracked the gait trajectory in both autonomous torque-profile regimes. This tracking enabled the exoskeleton to apply the appropriate magnitude and timing of its assistive torque, allowing the three participants to comment on which mode of exoskeleton actuation they preferred. The estimated gait phases (**Figure 8**) for the biological profiles of each participant span the same time range as in **Figure 6** and **Figure 7**.

B. Preliminary Evaluation of User Preference

Following these trials, each user evaluated which form of control they preferred, given the choice between direct control, autonomous biomimetic torque, and autonomous user-based torque.

Across all three participants, the use of autonomous over direct user torque application was preferred. However, among participants, there was a clear split between those who

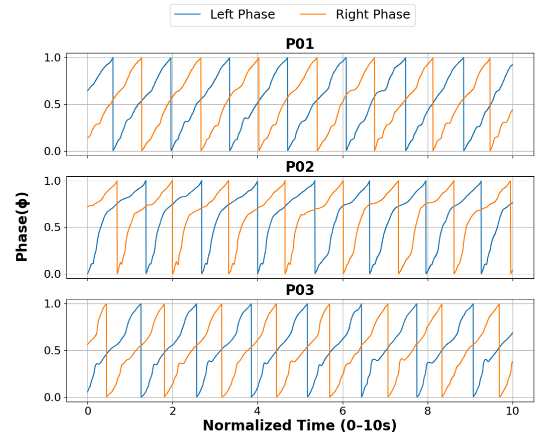

Fig. 8. Estimated Phase vs. Normalized Time.

preferred user-based and those who preferred biomimetic torque profiling. Two of the three participants preferred the biomimetic torque to their customized user torque profile. These two participants stated that the biological torque profile ”felt more natural and stable than [their] user profile” and that said torque felt more ”natural” in the positive and ”felt worse” in the negative. The participant who preferred their custom torque profile strongly liked it and stated that they ”felt the most comfortable walking in the exoskeleton” when this profile was applied. Interestingly, the users who preferred biological torque when applied autonomously still produced a distinctly non-biological torque profile when holding the triggers. Though this preliminary trial of n=3 does not allow for us to make a statistical claim on which profile the majority of users would prefer, this does highlight that users can detect a difference between their custom torque profile and the biological torque profile. This ability to distinguish between torque profiles, along with preliminary evidence that user preferences vary across autonomously applied profiles, supports continued investigation in future trials.

IV. Conclusion

User preference is critical to the commercial success of powered exoskeletons. These early results suggest that user preference for autonomous behavior may drastically differ from their preference when they have direct manual control.

Across three participants, autonomous torque was generally preferred, with biomimetic profiles described as more “natural” only when well-aligned but less favorable otherwise. However, due to the limited number of user trials, these findings remain purely observational, and no statistical claims can be made. Notably, the sensitivity of biomimetic performance to alignment, along with the variability in user perception, suggests that approaches incorporating direct user control may offer a more robust and adaptable path forward by preserving user agency and accommodating individual preference.

Although the current EKF model was able to track the distinct gait progressions of each participant, the phase progression deviated from the typical linear approximation of phase rate. Future work could involve modifying the current measurement model to account for altered motion kinematics.

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