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Enhancing the Efficacy of Lower-body Assistive Devices Through the Understanding of Human Movement in the Real World

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Abstract— **In previous studies, researchers have successfully measured walking in healthy able-bodied humans to create safe control strategies for lower body assistive devices. Measurements used to establish design requirements often come from testing and evaluation that takes place in laboratory settings during steady-state tasks, where participants often select movement strategies that minimize the cost of transport. However, human walking in these conditions does not necessarily represent the natural behavior of an individual in the real world. In this work, we conducted a study to characterize human walking in the real world. We combined week-scale free-living measurements of gait with in-lab data collection to: 1) quantify the proportion of steady-state walking in a population of healthy able-bodied adults, and 2) evaluate whether this population favors the selection of a range of walking speeds that minimize their cost of transport in the real world. We found that the majority of walking bouts contain mostly transient walking, suggesting that researchers should complement steady-state characterization with non-steady-state tasks. We also found that the most often used steady-state walking speeds for all participants were higher than the range that minimizes cost of transport, suggesting that individuals are influenced by more than energy economy when moving in the real world. Thus, when developing control strategies for these devices, researchers should consider a variety of optimization objectives to adapt for the multifarious situations of daily life.**

I. INTRODUCTION

Assistive devices, such as exoskeletons or prostheses, can greatly improve the mobility of an individual, with recent advancements continuing to enhance an individual's capabilities through new, innovative designs [1], [2], [3], [4], [5]. Naturally, human walking is an essential source of inspiration for the design of assistive devices; human walking represents the main mode of locomotion for humans in their daily lives. While the goal of assistive device development is to see the adoption of the technologies in the real world, the development of these assistive devices often occurs in laboratory settings. But measurements and observations in the lab may not be representative of the real world, leading to different conclusions about technology depending on the research setting.

First, walking behavior can vary in different environments. Gait features, such as walking speed, are known to differ inside versus outside the lab [6], [7], [8], along with overground versus on the treadmill walking [9]. Many factors have been identified as the sources of these changes in behavior including the white coat effect, which is an individual's change in performance caused by being observed in a laboratory [10], [11]. Additionally, the metabolic cost of walking can also be biased in the laboratory setting [9]. Taken together, these results suggest that laboratory experiments may not be representative of the natural behavior of individuals, and therefore limit the possible ecological relevance of advancements in the design of assistive devices informed by in-lab research.

Second, researchers often make assumptions about walking behavior in the lab that may not be representative of the real world. For example, most experiments designed to test and validate control strategies for lower-body assistive devices focus on steady-state gait on a treadmill or over short distances of overground walking [12], [13], [14], [15], [16], [17]. In these experiments, participants tend to be instructed to walk at a preferred speed [14], [16], [17] or at a standardized speed on a treadmill (often $1.25 m \cdot s^{-1}$) [18], [19], [20]. However, steady-state walking at a preferred speed may only make up part of the movement patterns used by an individual in the real world. Researchers have observed that individuals select a wide range of walking strategies in their daily life [21]. Orendurff et al. [22] found that most walks in a cohort of able-bodied healthy adults were short containing only a few steps, which might not allow someone to reach steady-state [23], [24]. Similarly, Glaister et al. [25] found that turning, a non-steady-state walking behavior, is ubiquitous during daily life. Recently, researchers have started to design controllers for these non-steady-state walking behaviors for lower-body assistive devices [26], [27], [28], and these systems are being evaluated outside of the lab. For example, Medrano et al. [27] showed promising results in highly uneven terrains, but the study presented results from only one participant. However, the validation of these methods is still predominantly conducted within the lab environment.

Finally, many studies that aim to model able-bodied gait or to tune lower-body assistive devices assume that humans will tend to select a walking speed that minimizes their cost of transport [29], [30], [31], [32], [33]. However, whether able-bodied healthy individuals favor movement patterns that minimize their cost of transport during daily life is still an open question. The many layers of complexity in real-world walking — from the external environment in which the human is moving (e.g., terrain, inside vs outside) [34], to social context and interaction — all likely influence how individual moves, along with energetic cost.

To address this gap, data need to be collected in the real world to characterize and quantify human walking behavior.

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Wearable sensors offer a compact solution that can be used to measure movement during daily life for weeks at a time [35], [36]. Because these devices enable the measurement of continuous streams of data over long periods, data collected with wearable sensors can offer unique insights into an individual's behavior. This technology enables the evaluation of human movement outside the laboratory that complements in-lab assessments. For example, wearable sensors have been used to quantify the level of mobility of individuals with lower extremity amputations [37], [38]. These ecological observations can then be used to guide the design of flexible controllers that can more closely replicate healthy able-bodied movement.

Building on this work, we propose a framework that fuses week-long walking data from wearable sensors with laboratory-based metabolic measurements to explain real-world walking behavior. Using this multi-scale hybrid approach, we 1) quantify the proportion of steady-state walking used by healthy able-bodied adults, and 2) investigate if this population favors a range of speeds during steady-state walking that minimizes cost of transport. The results of this study provide insight into the walking strategies employed by a cohort of able-bodied healthy adults and will help inform the design and control of lower body assistive devices to improve real-world walking capabilities.

II. Data Collection

A. Subjects and Recruitment

We recruited 10 subjects from the healthy population (5 females, 5 males, 24.1 ± 2.6 years, height 169.5 ± 9.5cm). Each participant electronically signed a consent form and this study was approved by the Institutional Review Board of the University of Michigan.

B. Experimental Protocol

1) Real-world data collection: Following an initial visit, participants were given a set of sensors and instructions to collect motion data during a week of free living. We chose a thigh-worn accelerometer (activPAL^{TM} [PAL Technologies Ltd., Glasgow, UK]) with a validated activity classification software to detect all walking instances during the week [39], [40]. Its format (23.5 × 43 × 5 mm), placement, light weight (9g), waterproof, and week-long battery life helped ensure high compliance across all participants. To capture foot kinematics, we used an inertial measurement unit (IMU) (Opal, APDM, [Portland, OR, USA]) with a 3-axis accelerometer, gyroscope, and magnetometer. It was attached with a fabric pouch secured with the shoe laces (Figure 1 - (A)). The system was configured to record at $100Hz$ to obtain a battery life of 8+ hours. Participants were instructed to recharge the sensor each night and could also opt-in to receive daily text reminders.

2) In-lab data collection: We collected level walking data on an instrumented split-belt treadmill (Bertec, [Columbus, OH, USA]) at 6 different speeds for 6 minutes each. A 2-minute resting period was allowed between each trial and the order of the speeds was randomized. Treadmill speeds were determined using the extracted range of speeds from the data collected during the real-world protocol. This range was adjusted during a warm-up session to adapt to the participant's level of comfort on the split-belt treadmill. Participants were equipped with the Cosmed K5 (COSMED, [Rome, Italy]), a portable indirect calorimetry system that measures the oxygen and carbon dioxide volumetric flow rate for each breath. The system consists of a small back-pack and mask worn above the subject's mouth and nose. Subjects were instructed to refrain from eating, drinking caffeine, and exercising 5 hours prior to the visit to avoid biasing the metabolic measurements. A 26-camera Vicon (Vicon, [Oxford, UK]) motion capture system measured the lower-limb kinematics using 16 markers sampled at $100Hz$. We used the plug-in gait lower body marker model from Vicon to determine marker placement. Force plate data from the instrumented treadmill were also collected at $1,000Hz$ sampling.

Stride length can be mapped to stride speed using a power model:

$$l = a.v^b \tag{1}$$

where a and b are heuristically determined model parameters [41], [42]. During treadmill walking, participants tend to select a more cautious walking strategy (e.g., shorter strides) to increase their stability [43]. Consequently, the relationship between kinematic parameters can be different when walking overground or on a treadmill. Thus, to bridge the gap between real-world and in-lab data collections, we used the parameters associated with the stride length-speed relationship found during the real-world data collection to select parameters for treadmill walking. Since we cannot easily enforce stride length on a treadmill, we leveraged the relationship between stride length, stride speed, and stride frequency f ($v = l{\cdot}f$) to enforce stride frequency in treadmill walking. We provided participants with a metronome beat to which they were instructed to synchronize their steps as best as possible (Figure 1 - (A)). The pairs of metronome frequency and treadmill speed $\{f, v\}$ were chosen to match the walking strategy observed during the real-world data collection. Before a trial, we made sure that the highest and lowest $\{f, v\}$ frequency/speed pairing were comfortable for the participant. Additionally, we checked that the participant was able to match the stride frequency for a given stride speed. We evaluated the efficacy of this method by comparing the relationships between stride speed and stride length obtained in the real world and in the lab.

III. Data Processing

A. Real-world data processing

We used the proprietary algorithm from activPAL to extract walking bouts. A walking bout is defined as the instance when an individual starts walking after a pause (either sitting or standing) until the start of the next pause. For each walking bout, we identified strides from heel strike events using the angular velocity from the foot-worn IMU. After correcting for the orientation, we smoothed the axis in

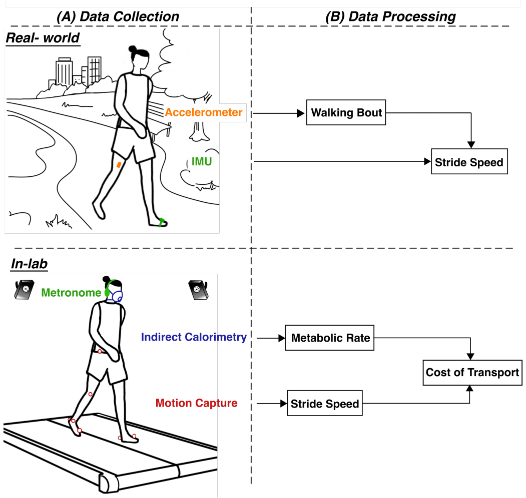

Fig. 1: Data Collection and Processing — (A) Data collection combined a week of data collection in the real world and an in-lab treadmill walking task. (B) Data processing methods were used to combine the different sensor streams to obtain stride speed profiles in the real world, and a map of cost of transport vs. stride speed in the lab.

the distal direction, aligned with the long axis of the foot, using a locally weighted scatterplot smoothing (LOWESS) method. Then, we used a peak detection algorithm on the signal to isolate strides. We only evaluated bouts with at least 5 strides to reduce potential errors in gait parameter estimation, stride detection, and the isolation of walking events by the activPAL proprietary algorithm. After separating out the walking bouts, we estimated gait parameters using the zero-velocity update (ZUPT) algorithm [44], [45], [46]. ZUPT is a validated method to obtain estimates of foot position from the integration of IMU data. It uses the assumption that the velocity of the foot on the ground is close to zero when walking to correct for the drift when integrating acceleration data to obtain velocity and position. We followed the implementation formulated by Rebula et al. [46] using the same hardware. Using the foot trajectory, we extracted stride length and obtained stride speed by dividing stride length by stride time (Figure 1 - (B)).

B. In-lab data processing

Foot strikes were obtained using the force plate data from the instrumented treadmill. Strides in which participants did not place their feet on each belt were discarded. We used the trajectory of the heel marker to measure stride length, as it appeared to be the one that moved the least and was the least obstructed among the foot markers given our camera setup. We calculated stride length by multiplying stride time by the speed of the treadmill belt (assumed constant), and we added the distance between two consecutive foot strikes from the same foot to account for the longitudinal movement of the participant on the treadmill. Stride speed was subsequently obtained by dividing stride length and stride time.

Each treadmill trial was 6-minutes long to allow participants to reach a steady oxygen consumption. We averaged the breath-by-breath measurements of oxygen and carbon dioxide to minimize the impact of measurement noise from the system. Then, we used the Brockway equation to calculate the whole-body metabolic rate [47]. We made sure the respiratory quotient never exceeded 1, to ensure the usability of the equation. The cost of transport was obtained by dividing the metabolic rate by stride speed and normalizing by body mass (Figure 1 - (B)).

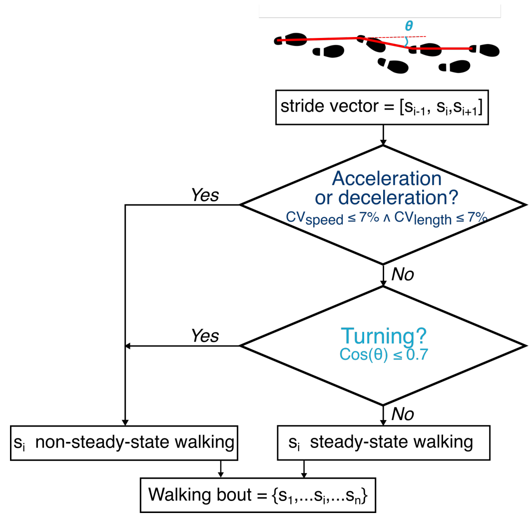

Fig. 2: Flowchart for the algorithm for identification of steady state. (CV: coefficient of variation)

IV. Analysis of Steady-State and Walking Economy

A. Defining and extracting steady-state strides

In this paper, when using the term steady-state, we are referring to dynamic steady-state during walking — steady-state walking can be understood as maintaining constant gait parameters, such as stride speed and stride length [23], [24]. Stopping, starting, or turning in a walking bout can lead to non-steady state gait. As such, we used gait parameters and the direction of strides to isolate steady-state walking in our real-world data. We iterated through a walking bout by extracting gait parameters and stride directions for three consecutive strides. We used the coefficient of variation (CV) of stride speed and stride length to determine acceleration and deceleration phases. We also compared the directions of the first and second stride to identify turning. The direction of a stride was calculated as a vector between the position of two consecutive heel strikes from the same foot. We conducted a sensitivity analysis to determine the thresholds used for CV of stride length and stride speed, and for cosine similarity and used a controlled in-lab walking task for validation. The algorithm is detailed in Figure 2.

We tested whether stride speed mean and standard deviation were significantly different between steady-state and non-steady-state. We used a multi-level model to account for the nested structure of the data with subjects, walking bouts, and the parameters (steady-state or not, and stride speed mean and standard deviation). We used R to select the model that explained the most variance using the Akaike Information Criterion.

TABLE I. Bout characteristics, and proportion of steady-state walking and energetically optimal (e.g. economical) strides.

	Total # bouts	Avg bout duration (min)	Avg strides per bout	Avg steady-state strides in bout	Total # strides	Percentage steady-state strides	Percentage economical strides within all steady-state strides
S1	180	1.9	73.5	44.5%	13,236	69.4%	42.2%
S2	207	1.3	46.0	54.3%	9,528	77.1%	17.5%
S3	30	6.3	282.1	59.5%	8,463	82.5%	71.4%
S4	126	4.1	182.1	63.3%	23,328	88.6%	4.9%
S5	229	2.6	113.7	55.2%	26,046	86.4%	24.6%
S6	260	1.6	55.8	35.3%	14,500	45.5%	37.4%
S7	110	3.1	140.2	62.4%	15,423	83.7%	18.0%
S8	163	4	178.2	52.5%	29,054	90.2%	27.7%
S9	202	2.3	95.3	49.0%	19,243	81.5%	58.4%
S10	214	2.1	73.7	41.6%	15,764	69.5%	43.9%
All Subjects	984	2.5	101.4	49.4%	174,585	79.7%	49.4%

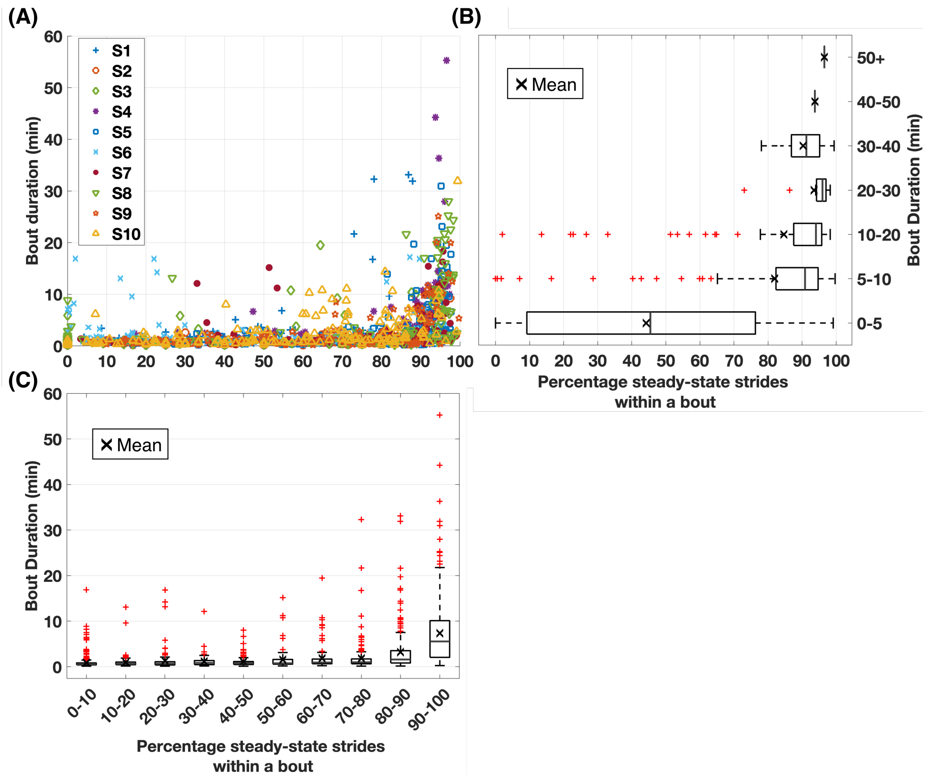

Fig. 3: Relationship between bout duration and percentage of steady-state strides within a bout — (A) Each dot corresponds to a bout. The different colors and marker shapes are for each participant. (B) We binned all participants' bout by their bout duration and looked at the percentages of steady-state strides within a bout for each bin. (C) We binned all participants' bout by their percentage of steady-state strides and looked at the bout durations for each bin.

B. Defining and extracting economical strides

We mapped cost of transport to stride speed for the in-lab data using a second-order polynomial. The minimum $+10\%$ of the fitted curves was determined as the energetically optimal speed range for an individual. We looked at the proportion of steady-state strides — since we obtained the cost of transport during steady-state walking on the treadmill — with a stride speed within the energetically optimal speed range.

We used a Wilcoxon signed-rank test to evaluate whether the average steady-state stride speed was significantly different from the energetically optimal speed for each individual.

V. Results

First, we will look at whether the use of the metronome during the in-lab walking task successfully led participants to adopt the walking strategy they used in the real world. Then, we will quantify the amount of steady-state walking and how often participants selected stride speeds within the energetically optimal range. For this part of the analysis, we examined the results for all strides but also for strides grouped by bouts — a bout constitutes several strides (at least 5 in our case). In other words, this allowed us to understand what constitutes the movement when someone starts walking (within a bout) as opposed to looking at all strides equally.

A. Real-world versus in-lab walking strategy

We found a mean absolute difference in the coefficients a and b of the power model (Eq (1)) of 3.6% and 16.1% respectively. The difference in coefficient b leads to a rotation of the power curve that indicates (as expected) a decrease in stride length for higher stride speeds (approx. $< 1m \cdot s^{-1}$) on the treadmill. The largest discrepancies represent differences of around $0.1m$ in stride length for a given stride speed and

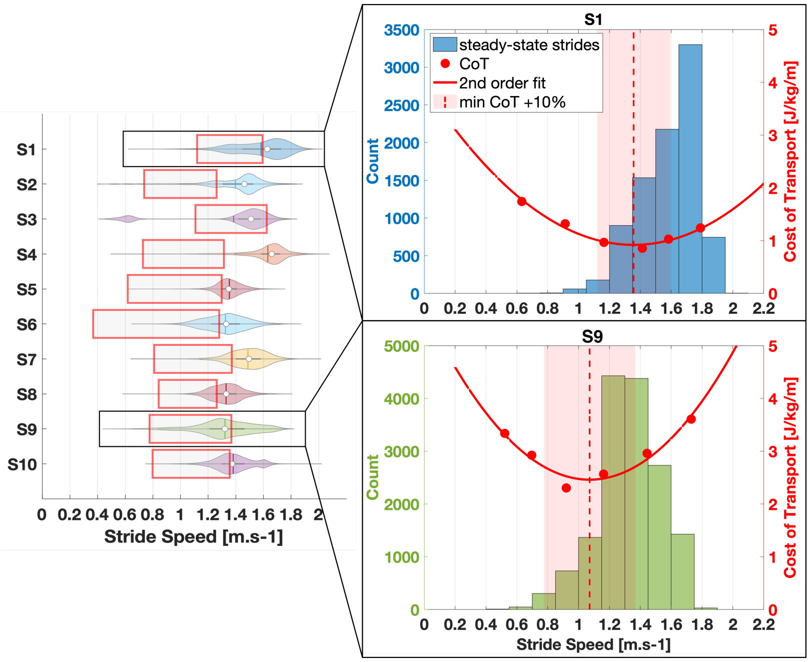

Fig. 4: Analysis of walking economy — We observe that the distribution of real-world steady-state stride speeds for each participant is higher than the range of speeds within $+10\%$ of the minimum cost of transport (CoT). Zooming into two participants, we can see how the economical range is situated compared to the peak of the real-world stride speed histogram.

are mostly concentrated on the extremes (e.g., very slow or very fast speeds).

B. Steady-state and non-steady-state

We detected a total of 174,585 strides among all participants. We classified approximately 80% of these strides as steady-state gait strides (Table I). A multilevel model was used to examine the difference between mean and standard deviation for steady-state and non-steady-state stride speed, controlling for the walking bout, and the subject. Fixed effects revealed that whether a stride was steady-state or non-steady-state predicted both mean ($b = 0.1, t(1043) = 31.5, p < 0.001$) and standard deviation ($b = -0.06, t(1043) = -29.68, p < 0.001$). In other words, steady-state stride speeds tend to have higher means (between $+0.12m{\cdot}s^{-1}$ and $+0.34m{\cdot}s^{-1}$) and lower standard deviations (between $-0.13m \cdot s^{-1}$ and $-0.24m \cdot s^{-1}$) than non-steady-state stride speeds.

We identified between 30 and 260 bouts for each subject (Table I). Within these bouts, $\sim 55\%$ had a duration of less than one minute (Figure 3-(A)) and contained less than 25 strides. For all participants, we found $\sim 20\%$ of the bouts contained no steady-state strides, which corresponded to bouts with an average duration of 0.7 minutes. As expected, we see a trend between bout duration and the proportion of steady-state strides (Figure 3-(B) and (C)). The data indicate that longer bouts (> 15 minutes) are more likely to contain steady-state strides for more than 80% of the overall strides for those bouts. However, only 44 bouts across all participants were longer than 15 minutes. Additionally, we notice that short bouts (< 5 minutes) — which constitute 87% of all of the bouts — have a large range of steady-state stride percentages within the bouts (from 0% to almost 100%)(Figure 3-(B)).

C. Cost of transport minimization

We obtained good fits for the relationship between stride speed and cost of transport. The models presented R^2 and RMSE values ranging from 0.70 to 0.98 and $0.05J/kg/m$ to $0.38J/kg/m$ respectively. The speed that minimized cost of transport ranged from $0.82m \cdot s^{-1}$ for S6 to $1.37m \cdot s^{-1}$ for S3. S6 presented the largest range of speeds minimizing cost of transport (from $0.37m \cdot s^{-1}$ to $1.3m \cdot s^{-1}$) (Figure 4). Average steady state speeds used in the real world were significantly larger than the energetically optimal speed (median = $0.35m \cdot s^{-1}$), $V = 55$, $p = 0.003$, $r = -0.95$. The difference ranges between $0.05m \cdot s^{-1}$ and $0.58m \cdot s^{-1}$ which corresponds to increases of 0.3% and 40% in cost of transport respectively. Overall, between 4.9% (S4) and 58.4% (S9) of all strides were economical (Table I). Only S3 and S9 used slightly more economical speeds.

VI. Discussion and Future Work

Lower-body assistive devices have greatly improved with advancements in robotic technologies. Bio-inspiration is an essential driver for innovation and it is crucial to further the understanding of realistic daily-life movement, like walking, to determine ecologically valid design requirements. In this study, we looked at two common walking modalities researchers have focused on when tuning, testing, and creating design requirements for lower-body assistive devices in the lab: steady-state walking and energetic optimization when walking. We found that 1) a meaningful portion of the ensemble of strides in the real world were not at steady-state, 2) walking bouts were predominantly short with only a few strides and were mostly non-steady-state, and 3) the majority of stride speeds selected in the real-world are significantly higher than the speed that minimizes the cost of transport. These findings suggest that the behaviors researchers prioritize in the laboratory setting are not predominant in the real world. This new insight can be leveraged toward new experimental paradigms for the design and testing of lower-body assistive devices.

A. Non-steady-state walking

A large proportion of designs and control strategies for lower-body assistive devices are conducted in the laboratory setting during steady-state walking. However, we found that only 80% of all strides across the participants were at steady-state. The majority of these strides came from long duration bouts enabling more time at steady-state (Figure 3 - (B)). However, the majority of bouts in the real world are short with few strides ($\sim$ 55% shorter than 1 minute with less than 25 strides) (Figure 3 - (A)). Further, most bouts contained a majority of non-steady-state strides (Figure 3). In other words, these results suggest that most walking tasks result in walking that contain changes in stride speed, stride length, and direction of motion. This supports the findings by Glaister et al. [25]: short bouts of walking are prevalent and lead to many turns in daily life, which consequently lead to a high amount of transient walking. These results suggest that researchers should continue and perhaps prioritize the development of adaptive controllers that incorporate the modelling of non-steady-state motions such as stopping and starting [48], [49].

B. Walking economy

It is often hypothesized that humans tend to select a walking speed that minimizes their cost of transport. As such, paradigms such as the human-in-the-loop model have been used to tune prostheses and exoskeletons that focus on optimizing the energetic cost of walking [20], [18], [50]. Yet, we found that participants selected steady-state stride speeds within the energetically optimal speed range less than 50% of the time. Overall, the steady-state stride speeds participants preferred were higher than what was estimated as energetically optimal (Figure 4). Medrano et al. reported that participants (N = 10) could notice changes of around 20% in cost of transport when walking on a treadmill with a lower-body exoskeleton [20]. In our data the difference in stride speed led to an average of 12% increase in cost of transport. It is unclear whether this difference is noticeable for individuals in the real world and whether it matters for the given distance people travel. Humans may have alternative objectives, along with energetic costs, that are used to select movement patterns in the real world. Since only $\sim$ 6% of the walks were longer than 10 minutes, an individual does not necessarily need to optimize for energy. For example, an individual using walking as a mode of transportation (ex: commuting) might optimize for time instead of energy efficiency (e.g., arriving faster). Similarly, researchers have shown that humans tend to optimize for stability over minimal energy consumption when walking on uneven terrains [34]. These results demonstrate the importance of considering multi-objective optimization paradigms when creating control strategies for assistive devices [51].

C. Variability in walking behavior

The inherent nature of human movement and walking in the real world is highly variable. However, the laboratory setting does not allow for much variability in human movement, particularly on the treadmill. Results presented here show that humans display a multitude of walking modalities, from steady-state to non-steady state. Even within steady-state walking, participants often select a range of walking strategies. The data collected here can be leveraged to inform data-driven models such as in [52], where measurements of daily-life human behavior were used to create ecologically valid assistance using an exoskeleton in the real world.

D. Limitations and future work

There are limitations and caveats to our experimental design that should be taken into consideration. Firstly, it is important to note that the mapping of energetic cost to walking speed was done in the lab, on the treadmill, and used to draw conclusions on real-world data. However, to bridge the gap between the laboratory and the real world, we: 1) successfully enforced the walking strategy found in the real world on the treadmill, and 2) attributed a sufficiently large interval (10%) around the minimum cost of transport to make sure we captured an energetically optimal speed range. Several studies have successfully used arrays of wearable sensors to estimate steady-state walking metabolic cost [53], [54]. However, the number of sensors required could not realistically be used for a week. Further, expanding the sample size and population diversity should also be pursued, as our study involved only young healthy adults.

VII. CONCLUSIONS

In this study we used wearable sensors to continuously monitor healthy young adults at the week-scale, and found that this group did not prioritize steady-state or energetically optimal walking speeds. As such, future design and control strategies for prostheses, exoskeletons, and even bipedal robots, should consider a wider range of movement patterns when defining functional requirements. For future work, we will investigate the behavior of a larger participant sample size and potentially extend this analysis to clinical populations, such as lower-limb amputees. We are also interested in investigating how real-world scenarios could be effectively simulated in the laboratory environment.

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