Characterizing Intent Changes in Exoskeleton-Assisted Walking Through Onboard Sensors

Taylor M. Gambon, James P. Schmiedeler, and Patrick M. Wensing

***Abstract*— Robotic exoskeletons are a promising technology for rehabilitation and locomotion following musculoskeletal injury, but their adoption outside the physical therapy clinic has been limited by relatively primitive methods for identifying and incorporating the user's gait intentions. Various intent detection approaches have been demonstrated using electromyography and electroencephalography signals. These technologies sense the human directly but introduce complications for donning/doffing the device and in measurement consistency. By contrast, sensors onboard the exoskeleton avoid these complications but sense the human indirectly via the human-robot interface. This pilot study examines if onboard sensors alone may enable identification of user intent. Joint positions and commanded motor currents are compared prior to and after changes in the user's intended gait speed. Preliminary experimental results confirm that these measures are significantly different following intent changes for both able-bodied and non-able-bodied users. The findings suggest that intent detection is possible with onboard sensors alone, but the intent signals depend on exoskeleton control settings, user ability, and temporal considerations.**

I. Introduction

Robotic exoskeletons, such as the EksoGT in Fig. 1 (Ekso Bionics), have the potential to restore mobility and independence following musculoskeletal injury. As an alternative to body-weight supported treadmill training, the exoskeleton's trajectory-tracking control system relieves the burden on therapists to manipulate the user's limbs and allows the user to practice repeatable overground locomotion patterns. As an alternative to the wheelchair, the rigid exoskeleton structure also provides the support necessary for the user to interact with the community from a standing position and to exercise core strength and stability. For effective shared control with the user, though, the exoskeleton must recognize, interpret, and match the user's intended movements.

Soft exoskeletons, or exosuits, have successfully utilized kinematic and gait event-related cues to coordinate the exoskeleton with human motion, achieving reductions in the metabolic cost of walking [1], [2]. Soft exoskeletons, however, act in a transparent manner for most of the gait cycle, allowing the user to freely control gait events by deflecting the device's elements. This flexibility allows the user to automatically achieve changes in intent-related parameters like gait speed and step length, but it does not provide enough support for early-stage gait rehabilitation. Rigid exoskeletons provide the appropriate support, but are more restrictive, requiring the human and exoskeleton to work together to achieve the same changes in gait characteristics. Some work has leveraged models of the dynamic interaction between the human and exoskeleton to lower the resistance of a joint to motion [3], [4]. Other work provided actuation at each exoskeleton joint in proportion to the electromyographic (EMG) activity of muscles associated with the joint [5]. While implemented on rigid exoskeletons, these methods automatically react to the user's intent instead of identifying and mediating it. As a result, these methods are inappropriate for gait rehabilitation where the exoskeleton must aid the user in following a healthy gait trajectory.

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*All authors are with the Department of Aerospace and Mechanical Engineering, University of Notre Dame, 365 Fitzpatrick Hall of Engineering, Notre Dame, Indiana tgambon@nd.edu

Fig. 1. EksoGT operator using Lofstrand crutches

Other exoskeleton control strategies involve explicit identification of the user's intent by directly sensing the human. These methods provide varying levels of user-intent matching and comfort, from manual button-push input from the user to finite state machines that identify discrete gait modes [6]–[9]. Finite state machines have notably proven effective with populations that have abnormal or minimal motor control [6], [10]. The most popular method of finite-state intent detection has been through machine learning strategies for automatic pattern recognition. With these approaches, a machine learning model is trained on labeled data collected about the human and/or the exoskeleton (e.g., EMG, electroencephalography (EEG), motor position or current trajectories) [11]–[15]. Automatic pattern recognition based on EMG or EEG relies heavily on the consistency of the input sensors [14], [16]. The required consistency is difficult to achieve with donning/doffing the device between gait-training sessions and even across the time spent in a single session as the user moves and perspires. One approach to achieve the requisite consistency is to rely on sensors already integrated with the exoskeleton instead of taking measurements directly from the human. Commercial exoskeletons such as the EksoGT collect commanded motor currents and positions from the motor controllers and encoders. Since humans normally adjust joint kinematics and kinetics to realize changes in gait speed [17], [18], these existing sources of data are likely to be indicative of changes in the user's gait-speed intent.

It is unclear, however, how interaction with an exoskeleton influences normal human gait dynamics and how this impacts measurements taken onboard the exoskeleton. The exoskeleton's control law or gait assistance strategy likely influences the user's ability to change gait speed. For instance, two of the EksoGT's gait modes are Free and Adaptive. The Free mode provides continuous support similar to gravity compensation, but does not track a trajectory; therefore, users should be more capable of achieving gait changes according to their intentions. Adaptive mode, on the other hand, tracks a trajectory for the swing leg, which may suppress a user's ability to change gait. Kinematic gait changes achieved in Free mode that are not present for the same intention change in Adaptive mode represent intended gait changes suppressed by the trajectory tracking. While rejecting those kinematic perturbations, though, the commanded motor currents in Adaptive mode may still indicate the intended change. The presence of these "intent signals" in measurements already logged by the exoskeleton could have applicability for an intent detection strategy that does not involve extra equipment such as that required for EMG and EEG sensing. The nature of these intent signals likely depends on the control strategy of the exoskeleton, the type of intent change, and the strength and ability of the exoskeleton user.

This pilot study characterizes aspects of the human/exoskeleton interaction in response to user intent changes. Measurements of exoskeleton motor positions and commanded motor currents were collected before and after users made a change in intended gait speed. Responses were characterized for both an able-bodied and a non-able-bodied subject using two gait assistance modes of the EksoGT. Results suggest that subjects were less able to achieve kinematic gait changes in Adaptive mode, but the commanded motor currents still indicated their intent. The gait assistance mode, the type of intent change, and the user's capability all affected the presentation of possible intent signals.

II. Methods

A. Data Collection

Two human subjects with substantial experience using the EksoGT exoskeleton gave their informed consent and participated in the IRB-approved study; one had a chronic, incomplete spinal cord injury, hereafter referred to as NAB (non-able-bodied), while the other was able-bodied, AB. Subjects donned the EksoGT and used Lofstrand crutches as stability aids.

To begin a trial, subjects walked naturally down a 6m long walkway in the exoskeleton before being given a pseudo-randomized command to speed up, slow down, or make no change in gait. Subjects took approximately 9 strides with each leg per trial, and the commanded intent change was given as the subject passed approximately halfway through the walkway. This ensured that the subject had several steps to get up to steady-state speed prior to the intent command and several steps after the intent command before needing to slow down to stop.

Trials continued until three repetitions of each command were completed for each of Adaptive and Free modes. Both gait assistance modes prevent collapse of the joints during stance to ensure the user stays upright. In Adaptive mode, the exoskeleton employs predefined gait trajectories for the swing phase, providing corrective input at the joints when the user deviates from the trajectories. In the double support phase, Adaptive mode waits for the user to shift weight to the leg entering stance and to kinematically prepare the leg exiting stance before initiating the next swing phase. In Free mode, the exoskeleton only provides continuous support and the user may initiate swing at any time. The exoskeleton recorded the commanded currents and angular positions of the motors at the hip and knee joints and the readings of force sensors in the feet. By fusing IMU data from the torso with joint angle measurements, the exoskeleton also estimated the absolute position of each hip. While the commanded currents may not precisely correlate to exoskeleton joint moments, this paper uses changes in their values from trial to trial as a proxy to capture changes in the interaction moments between the operator and the device.

B. Data Processing

All signals were filtered with a fourth-order low-pass Butterworth filter (6Hz cut-off frequency). Heel strike events were defined when the filtered foot force signal exceeded a threshold. Data were separated into heel-strike-to-same-leg-heel-strike gait cycles. For each trial, a maximum of two strides before and two strides after the command were retained for processing. When the trial's initial or final cycle was within two strides of the command, that cycle was discarded to minimize the effect of the subject beginning at or returning to rest. Stride time was calculated from the first to second heel strike of the same leg. Hip progression was calculated as the difference in the forward position of the ipsilateral hip from heel-strike to heel-strike. Left and right strides were combined for each measure assuming subjects were left-right symmetric, and for plotting, strides were normalized to the fraction of gait cycle.

Next, each stride was reduced to 100 data points, one for each hundredth of the gait cycle, by averaging the data points within each of 100 evenly-spaced bins (Fig. 2 B). Inter-stride averages and standard deviations were calculated for every bin. One hundred one-way ANOVAs were performed to identify statistically significant differences between the pre- and post-command data for each bin ($p<0.01$). By performing an ANOVA for each bin individually, the statistical analysis was independent of time (Fig. 2 C). There were an average of 11 (min 9, max 12) strides in each of the ANOVA comparison groups. The number of bins with statistically significant differences were summed across all trials for

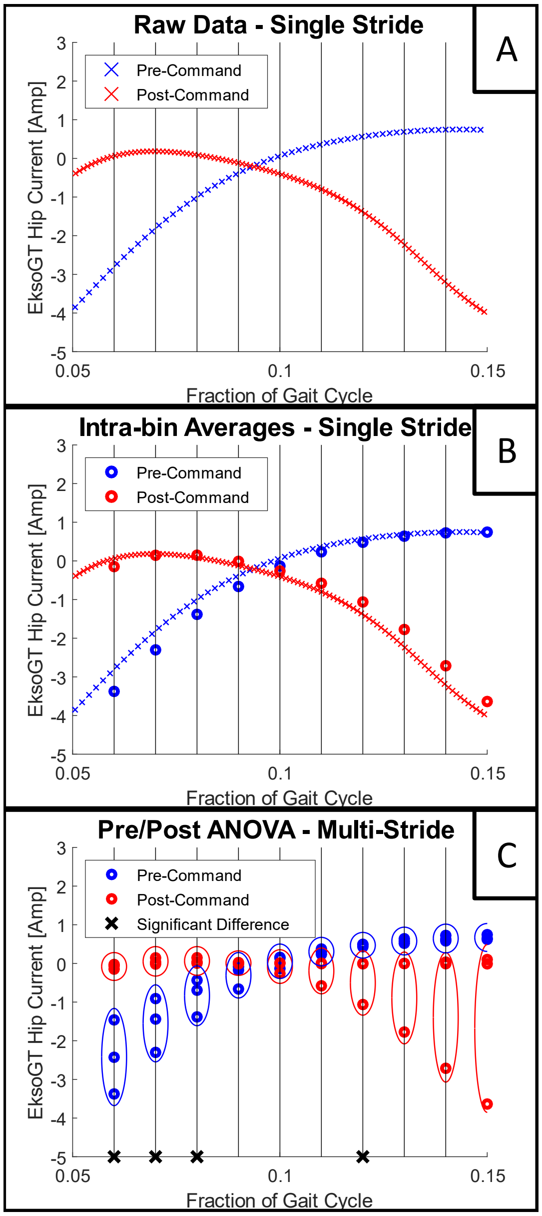

Fig. 2. Data processing: (A) data from example strides before (blue) & after (red) the command; (B) data reduction by averaging data points in every hundredth-of-the-gait-cycle bin; (C) one-way ANOVAs performed on multi-stride data within each percentage bin. Statistically significant results ($p<0.01$) indicated by a black X on the x−axis, as in the first 3 and the seventh bins for this example.

commanded current and joint measures. A one-way ANOVA was also used to identify statistically significant differences in stride time and hip progression post-command. For each No Change trial, additional angle and moment reference trajectories were graphed for the knee and hip using data from individuals walking normally without an exoskeleton at a higher speed than the subjects in this study walked [19].

III. Results

A. *Free Mode*

In Free Mode, both subjects achieved the intended gait changes by altering stride time, hip progression, or both (Table I). Neither stride time nor hip progression were significantly different following the No Change command. Stride time was significantly longer and hip progression was significantly shorter following the Slow Down command. Following the Speed Up command, stride time was significantly shorter, but hip progression was not significantly changed. The Slow Down command caused a significantly lower flexion angle (8-13°) for both the hip and knee in early stance of each subject (Figs. 3 and 4 C&D). For AB, the Speed Up command caused an increase in the maximum knee flexion angle (11.7°) and a slight phase lead of the hip angle in early stance (Figs. 3E and 4E). For every intent command, NAB had fewer significant differences than AB (Table II). AB had more significant differences at the knee than at the hip, but NAB had more significant differences at the hip than at the knee. Both subjects exhibited statistically significant differences post-command in both the commanded motor currents and joint kinematics (Figs. 3 and 4), but the number of significantly different percentage bins was greater for kinematic measurements (Table II).

TABLE I

Average stride time in seconds (T) and average hip progression per stride in centimeters (HP) pre- and post-command. Statistically significant differences post-command are indicated by * ($p<0.01$).

Subject	Gait Mode	Trial	Pre-Command		Post-Command	
			T [s]	HP [cm]	T [s]	HP [cm]
AB	Free	No Change	1.44	85	1.41	84
		Slow Down	1.33	89	**2.62***	**70***
		Speed Up	1.38	88	**0.97***	95
	Adaptive	No Change	1.23	72	1.23	73
		Slow Down	1.20	70	**2.08***	**62***
		Speed Up	1.28	71	1.20	**76***
NAB	Free	No Change	1.92	84	1.92	89
		Slow Down	1.99	84	**3.32***	**74***
		Speed Up	1.90	85	**1.64***	85
	Adaptive	No Change	1.49	77	1.43	77
		Slow Down	1.47	76	**2.23***	78
		Speed Up	1.48	76	1.39	**81***

TABLE II

Number of significantly different ($p<0.01$) percentage bins post-command for all trials

Gait Mode	Metric	AB		NAB	
		Slow Down	Speed Up	Slow Down	Speed Up
Free	Currents	66	29	9	0
	Angles	92	40	17	6
Adaptive	Currents	116	59	61	24
	Angles	42	51	54	14
Free	Knee	94	40	12	0
	Hip	64	29	14	6
Adaptive	Knee	67	36	73	13
	Hip	91	74	42	25

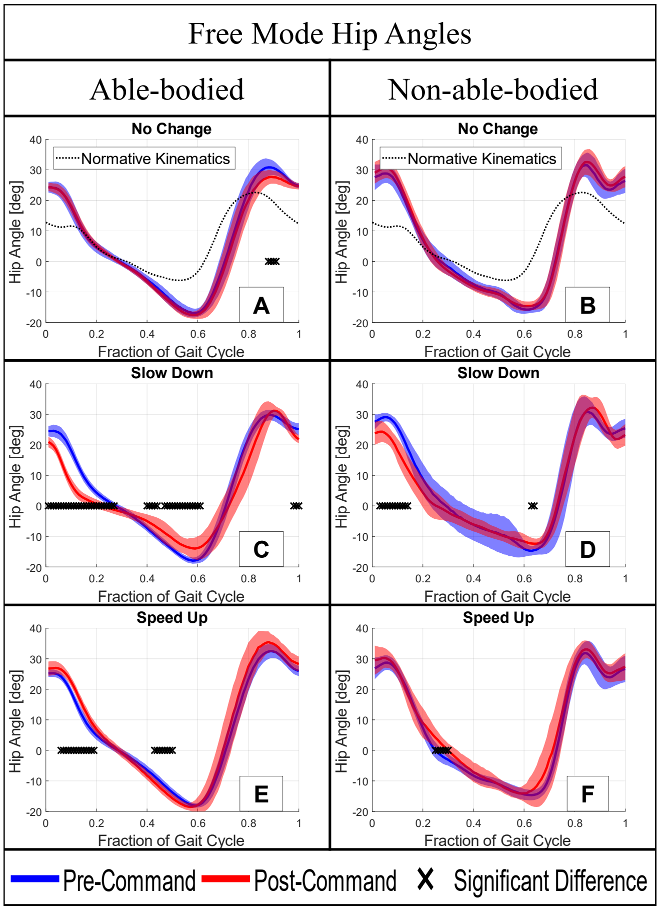

Fig. 3. Hip angle trajectories for Free mode trials. Pre- (blue) & post- (red) command data shown with solid lines indicating inter-stride averages & shadowed regions indicating inter-stride standard deviations. Dotted lines on No Change trials are normal joint kinematics [19].

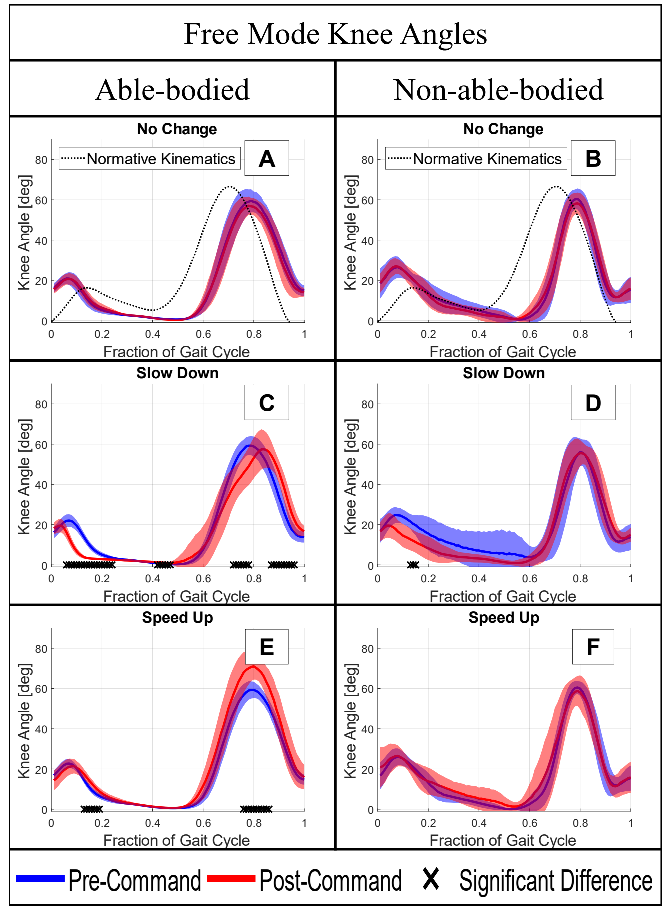

Fig. 4. Knee angle trajectories for Free mode trials. Pre- (blue) & post- (red) command data shown with solid lines indicating inter-stride averages & shadowed regions indicating inter-stride standard deviations. Dotted lines on No Change trials are normal joint kinematics [19].

B. Adaptive Mode

In Adaptive Mode, both subjects also achieved the intended gait changes by altering stride time or hip progression, but only AB altered both (Table I). Neither the stride time nor the hip progression were significantly different following the No Change intent command. The stride time was significantly longer following the Slow Down command, and the hip progression was significantly longer following the Speed Up command. The hip progression was significantly shorter following the Slow Down command only for AB. The Slow Down command caused increased commanded hip extension/flexion current in the first/second half of the gait cycle (Fig. 5 C&D). Despite the lack of reduction in gait cycle duration, the Speed Up command still caused increased commanded hip flexion/extension current in the first/second half of the gait cycle (Fig. 5 E&F). AB had more significant differences at the hip than at the knee, but NAB had more significant differences at the knee than at the hip. Both subjects exhibited statistically significant differences post-command in both the commanded currents (Figs. 5 and 6) and joint kinematics, but the number of significantly different percentage bins was greatest for commanded currents (Table II).

IV. Discussion

A. Effects of Exoskeleton Control Mode

For both Free and Adaptive modes, the small number of significant differences following the No Change command confirms that the gait changes following the Speed Up and Slow Down commands were not simply reactions to the experimenter's voice. The greater number of significant differences for the Slow Down trials indicates that this intention was more distinguishable than Speed Up using the commanded current and joint angle metrics. Across all gait modes and joints, the Slow Down command generally decreased joint range of motion, while the Speed Up command generally increased joint range of motion. These similar, but opposite changes for Speed Up and Slow Down are expected for walking without an exoskeleton [18]. Changes to the shapes of the kinematic trajectories were not as dramatic as the changes in stride time.

Since the control strategy in Adaptive mode attempted to correct deviations away from the prescribed trajectory during swing, the intent command caused more differences in the commanded currents and fewer differences to joint kinematics than it did in Free mode. Contrary to the hypothesis that the Adaptive mode's trajectory-based control might mask

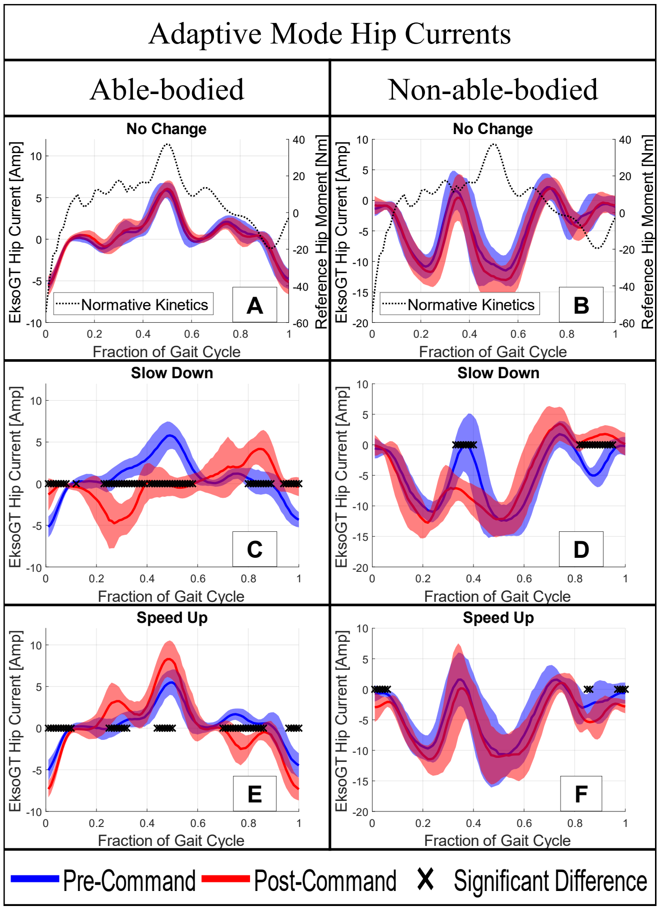

Fig. 5. Commanded hip current trajectories for Adaptive mode trials. Pre- (blue) & post- (red) command data shown with solid lines indicating inter-stride averages & shadowed regions indicating inter-stride standard deviations. Dotted lines on No Change trials are normal joint moments [19].

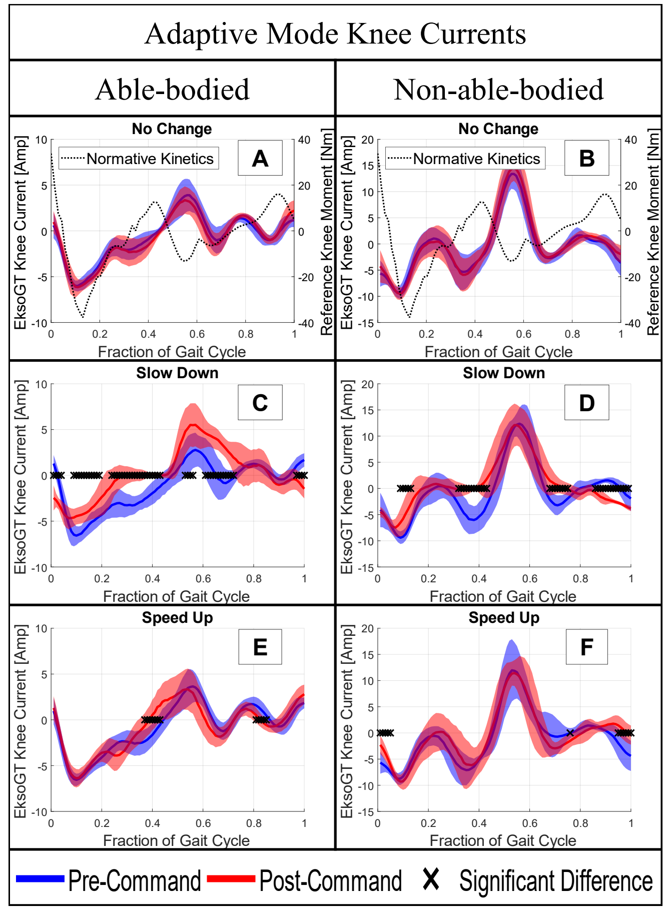

Fig. 6. Commanded knee current trajectories for Adaptive mode trials. Pre- (blue) & post- (red) command data shown with solid lines indicating inter-stride averages & shadowed regions indicating inter-stride standard deviations. Dotted lines on No Change trials are normal joint moments [19].

the user-intent signal, slightly more statistically significant differences were found post-command for Adaptive mode trials than for Free mode trials. The intent signal, therefore, is not only available through these measurements, but may actually be stronger for trajectory-based gait assistance.

Subjects were able to increase stride time for all Slow Down trials, but were unable to decrease stride time for Speed Up trials in Adaptive mode. Compared to Free Mode, in Adaptive mode subjects walked with shorter stride times and shorter hip progressions before any commands were given. To speed up, one must decrease stride time, increase stride length, or do both. Since subjects were already walking with shorter than normal stride times, they sped up through increased hip progression (presumably increasing stride length) instead. A parallel argument applies to the Slow Down trials for NAB. To slow down one must increase stride time, decrease stride length, or both. Since NAB was already walking with shorter than normal hip progression, NAB decreased speed by increasing stride time instead. These trade-offs suggest that when subjects change speed while walking in the trajectory-based assistance mode, they tend to do so in a way that approaches their more natural gait characteristics as exhibited in Free Mode.

B. *Effects of User Ability Level*

The commanded hip current trajectory for AB in the No Change trials shares many of the same peak locations with the hip moment trajectory for an individual walking without an exoskeleton [19] (Fig. 5). The same measure for NAB did not line up with normal walking hip moments. In particular, NAB had large commanded extension currents at roughly 0.25 and 0.50 of the gait cycle. These commanded extension currents may be an attempt to keep the subject upright at midstance and propelled forward at toe-off given the user's reduced strength. NAB had generally higher commanded currents than AB at both joints. Both subjects had joint trajectories in Free mode that were similar to the reference trajectory [19]. The peak hip angles, however, were more extreme than the reference. For all metrics and all gait modes, AB generally had more statistically significant percentage bins post-command and less step-to-step variance. The increase in variance for NAB could possibly be due to spastic disturbances to the gait, as are common for individuals with SCI. NAB was less able, but not unable, to express changes in intended gait. An onboard sensor-based intent-detection algorithm is, therefore, potentially viable for those

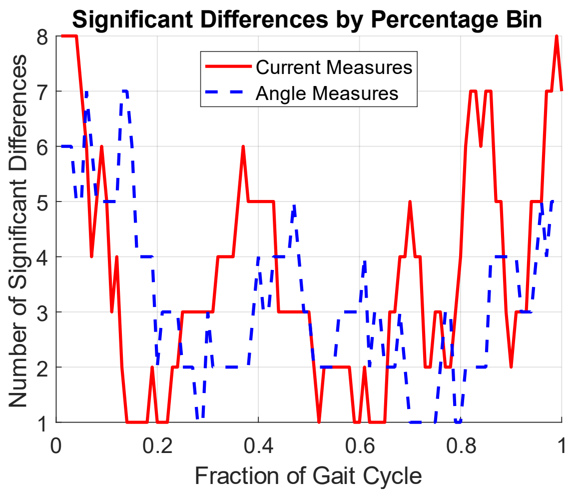

Fig. 7. Number of statistically significant differences in each percentage bin of the gait cycle, summed across trials & reported by metric (current/angle).

with limited mobility.

C. Temporal Considerations for Detecting Intent

For both subjects, all trials, and all metrics, the gait cycle phases most sensitive to changes in intent were transitions to and from stance (0-0.1, 0.3-0.5, and 0.9-1 of the gait cycle). Again, gait speed changes involve changes in stride length, stride time, or both. To modulate stride time, humans tend to modulate the duration of stance more than that of swing [17]. Step length is set at late swing/early stance by placing the swing foot on the ground, and the duration of stance is set at late stance/early swing by the timing of swing initiation. For changes in gait speed, it is logical that these portions of the gait cycle would be most affected.

While the significant differences in both the commanded currents and joint angles lagged behind the user's intent change, the currents became significantly different earlier in the gait cycle than the joint angles (Fig. 7). Since the commanded currents indicate an intent change closer to the true intention change, faster intent detection might be achieved by monitoring current measures than by monitoring kinematic values. Fast intent detection is desirable since an exoskeleton response that lags the intended motion by as little as 300ms can be perceived by the user [20].

V. CONCLUSION

Both the able-bodied and non-able-bodied subjects were able to express their intentions to increase/decrease walking speed in the exoskeleton through changes in joint kinematics and/or commanded joint motor currents in both gait assistance modes. While the subjects' baseline trajectories were different, they responded in similar ways to each intent change. A future user intent identification algorithm for a trajectory-tracking gait assistance controller should emphasize joint currents since they are more sensitive to intent changes overall and respond to intent changes earlier than do joint angles. Specifically for gait speed changes, an algorithm should monitor transitions between stance and swing. The interplay between hip progression and stride time appears to be especially indicative of the user's preferred gait style. Overall, the findings suggest that onboard sensors may be used for intent detection, but that the strongest intent change signals may appear on different sensors and at different times based on exoskeleton settings and the user's ability.

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