Emergent Gait Strategies Defined by Cluster Analysis When Using Imperfect Exoskeleton Algorithms

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***Abstract*—In operational settings, lower-limb exoskeletons may experience errors where an expected torque is not applied, impacting a user's gait strategies. In this study, we introduced an exoskeleton control algorithm with five different fixed error rates up to 10% error (90% accuracy). Participants ($N = 22$) walked with a bilateral ankle exoskeleton while completing a targeted stepping task. We assessed the impact of exoskeleton error rates on joint kinematics, muscle activation, and task performance using a k-means clustering algorithm ($k = 5$) to define gait strategies, which were interpreted in the context of human-exoskeleton fluency. One of the five emergent strategies was considered fluent, where users minimized muscle activation and aligned with the exoskeleton's goal of reducing metabolic cost while also maintaining acceptable task accuracy. Three strategies had acceptable task error, but involved increased muscle activation about the hip or ankle, thus negatively impacting human-exoskeleton fluency. One strategy minimized muscle activity, but had unacceptable task performance. Some users transitioned from fluent to non-fluent gait strategies after using the controller with higher error rates. Understanding emergent gait strategies can inform the development of exoskeleton algorithms that support appropriate gait strategies and system use.**

***Index Terms*—Biomechanics, error, exoskeletons, human-robot interaction, trust, wearable robots.**

I. Introduction

LOWER-LIMB exoskeletons have the potential to assist a human user's motor performance in laboratory environments by decreasing energy expenditure [1], [2]. In order for exoskeletons to be adopted in operational settings, they must be robust in uncertain environments. However, while exoskeleton control algorithms are continuously being developed and improved [3], [4], they are unlikely to be perfect and will experience errors. For instance, if gait phase estimation is inaccurate, the exoskeleton may miss an actuation during a stride and affect the user's gait. Gait strategies arise from the interaction between the human and exoskeleton. As the coordinated meshing of actions between the human and robot is defined as fluency [5], we can consider that human-exoskeleton fluency occurs when the human and exoskeleton's goals align. For example, the human decreasing muscular activity for exoskeletons designed to reduce energy expenditure. Thus, it is important to understand how exoskeleton errors impact gait strategies and human-exoskeleton fluency in order to inform performance requirements for exoskeleton algorithms. In this study, we focus on an ankle exoskeleton designed to reduce muscle activation and metabolic cost of able-bodied users for industry or defense applications.

Previous work has begun exploring the impact of imperfect control algorithms when walking with a lower-limb exoskeleton. Wu et al. [6] introduced random errors in exoskeleton operation by not applying an expected exoskeleton torque while participants completed a targeted stepping task. The study used an algorithm with approximately 2% error, or 98% accuracy, and found that step characteristics and task accuracy were not impacted by exoskeleton errors during missed actuations or strides with normal torque as users adapted their joint kinematics during errors to perform the stepping task. The level of error in the study was relatively low, so it is important to understand how more frequent exoskeleton errors will impact stepping strategies and task performance. For instance, it is possible that users will begin to increase muscle activation as they anticipate repeated errors, which is against the goals of the exoskeleton and would negatively impact human-exoskeleton fluency.

Gait strategies are constructed based on internal models, which are state-dependent representations of the dynamic properties of the limb in an environment that inform motor commands and predictions [7], [8]. Changes in internal models, or motor adaptations, may occur in response to visual or mechanical changes in the environment in order to minimize movement errors [9], [10]. Exoskeleton errors, such as loss of assistive torque for a stride, may induce movement errors and may prompt motor adaptations if errors consistently occur. It is currently unclear if there exists a threshold of error frequency where a user would modify their internal model when walking with an exoskeleton, resulting in different or less fluent gait strategies even during strides with nominal exoskeleton behavior.

In this study, we introduce an exoskeleton algorithm with defined error rates in order to understand how users respond to more frequent errors. We hypothesized that there would be time-dependent and algorithm-dependent changes in (1) joint kinematics, (2) muscle activity, and (3) task performance during the nominal steps. We also hypothesized that higher levels of error would cause larger changes in the above metrics. Gait strategies were defined using a k-means cluster analysis on a reduced set of gait features involving joint kinematics, muscle activity, and task performance. These results were interpreted in

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the context of human-exoskeleton fluency and can inform design requirements in operational settings.

II. Methods

A. Participants

Participants ($N = 22$, age $= 25.3 \pm 5.0$ years (mean $\pm$ SD), height $= 1.67 \pm 0.30$ m, mass $= 68.0 \pm 9$ kg, leg length $= 903.0 \pm 43.7$ mm, 12 female and 10 male) provided written informed consent. Participants were excluded if they had a lower extremity injury within the past 6 months or used an assistive walking device. The protocol was approved by the University of Michigan Institutional Review Board (HUM00217656).

B. Experimental Setup

Participants walked on a treadmill in a room equipped with a 10-camera optical motion capture system (Vicon Motion Systems Ltd, Oxford, UK). Reflective markers were placed on the participants according to the Vicon Plug-in Gait full-body model. Markers were adjusted for the exoskeleton by placing the lower limb markers on the lateral side of the exoskeleton when necessary. Electromyography (EMG) sensors (Cometa, Bareggio, Italy) were placed on the following 7 muscles on each leg: tibialis anterior (TA), soleus (SOL), medial gastrocnemius (GAS), biceps femoris (BF), rectus femoris (RF), tensor fasciae latae (TFL), and gluteus maximus (GMax). Motion capture and EMG data were collected at 100 Hz. Study participants wore the Dephy ExoBoot on both legs (Fig. 1) (DpEb504, Dephy Inc, Maynard, MA, USA). The ExoBoot applied torque at the ankle at push-off during the stance phase of the gait cycle, learned from 25 strides, which is the same as our previous study [6].

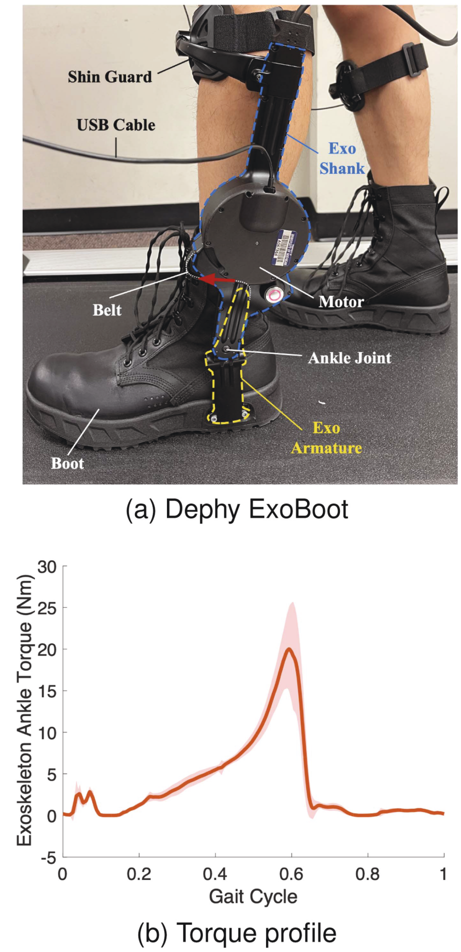

Fig. 1. (a) Powered bilateral ankle exoskeleton, which provides assistance by applying torque via the inelastic belt attached to the exoskeleton armature (DpEb45, Dephy Inc) [11]. (b) Torque profile applied at strides with nominal torque, where the peak torque is applied at approximately 60% of the stride.

C. Protocol

Anthropometric measures were collected prior to walking with the exoskeleton. Leg length was measured as the distance from the anterior superior iliac spine to the medial malleolus. Participants were given a target stepping task, which was a 320 mm-long region marked along the sides of the treadmill, while walking at a fixed speed of 1.2 m/s. A targeted stepping task was chosen as foot placement is an important component of gait in an operational environment, such as stepping off a curb or avoiding an obstacle on the ground. Task accuracy may then be used to assess prioritization of the task with respect to coordinating with the exoskeleton. Participants were asked to aim their heel at the center-line of the target region at the end of each stride. The stepping target length was chosen to be the length of the largest exoskeleton boot size, a Men's size 13.

Participants underwent a training protocol where they walked with the stepping target for 15 minutes with the exoskeleton powered on and torque applied during each stride (Fig. 1). The Dephy exoskeleton applied a plantarflexion torque about the ankle during mid-late stance and reverted to a zero-torque control modality during the swing phase. The controller adjusts the torque-angle relationship as a function of estimated walking speed, where dorsiflexion stiffness and plantarflexion passive power increase as walking speed increases.

Participants were then separated into two groups ($N = 11$ per group), which experienced the exoskeleton control algorithm with fixed error rates in different orders. There were 5 different error rates: 0%, 2%, 5%, 7%, and 10% error. This translates to controller accuracies of 100%, 98%, 95%, 93%, and 90%, respectively. Errors were introduced randomly throughout each trial by not actuating the exoskeleton for a single stride. We chose errors of no exoskeleton assistance rather than adjustment of control parameters for this study, as it has been shown that individuals may exhibit different sensitivities toward parameters such as actuation timing [11], which may introduce additional confounding factors. The exoskeleton algorithm also included a recovery period after each error, where the exoskeleton gradually ramps up from 0% to 100% between the error stride and the third stride after.

Participants experienced each controller twice for a total of 10 trials in one of two fixed orders. A fully randomized order was not selected as it creates difficulty in disambiguating between order and participant effects. By selecting two fixed orders, we can begin to examine the effect of order separate from participant variability. Group 1 started with a 0% error controller, increased to 10% error, and then decreased to 0% error. Group 2 started with a 10% error controller, decreased to 0% error, and then increased to 10% error. Details on the groups and control algorithms are shown in Table I. The number of strides for 2% error trials was higher than other trials to ensure an adequate amount of errors within the trial, verified via power analysis.

TABLE I
TRIAL ORDER OF EACH PARTICIPANT GROUP

Trial	Group 1	Group 2	Order
1	0% (0/300)	10% (30/300)	1
2	2% (12/600)	7% (21/300)	1
3	5% (15/300)	5% (15/300)	1
4	7% (21/300)	2% (12/600)	1
5	10% (30/300)	0% (0/300)	1
6	10% (30/300)	0% (0/300)	2
7	7% (21/300)	2% (12/600)	2
8	5% (15/300)	5% (15/300)	2
9	2% (12/600)	7% (21/300)	2
10	0% (0/300)	10% (30/300)	2

Notes: The percentages represent the error rate of each control algorithm and the ratios in parentheses show the number of errors to the number of total strides within a trial. An error consists of not actuating the exoskeleton for a single stride. The order represents whether the trial is the first or second time that a participant experiences an error rate.

D. Data Analysis

Gait cycles were segmented with a custom MATLAB script by using the heel marker data from motion capture to identify heel strikes. Absolute task error was calculated as the absolute value of distance between each heel strike and the center-line of the stepping target. Acceptable absolute task error was determined as $\leq$160 mm, which is half of the 320 mm-long target. Joint kinematics were calculated according to the Plug-in Gait model. Four metrics of interest were identified for each stride according to our previous study [6] – maximum hip flexion during swing, minimum knee flexion during loading response, maximum knee flexion during swing, and maximum ankle plantarflexion. These metrics were shown to be immediately impacted during strides with missed actuations, but did not change during strides with normal exoskeleton torque, which indicated that the users' gait strategies were not affected by 2% error in the previous study.

Only strides where the exoskeleton applied a normal torque were used in the analysis, as we were primarily interested in observing the effect of various error rates on gait strategies while the system was operating nominally. The joint kinematics metrics and task error of each trial were separated into 20 equal bins and averaged within each bin to observe time-dependent changes over a trial (20-length vector per metric).

EMG data were pre-processed using a high-pass 3rd-order Butterworth filter at 40 Hz, rectification, and a low-pass 3rd-order Butterworth filter at 10 Hz. Heel strikes identified from motion capture data was used to segment the EMG data to strides, then stance and swing were segmented using toe-off identified using the toe markers, respectively. The root-mean-square (RMS) values of each muscle in stance and swing were calculated for each stance and swing phase of each stride.

The mean of the RMS EMG values for last 60 strides of the training session was used as a baseline for each muscle. RMS EMG values of each trial were normalized by subtracting the corresponding baseline value, then dividing by that baseline value, thus creating %RMS EMG values. Similar to joint kinematics and task performance, only strides without errors were used for the analysis. A mean %RMS EMG value for each muscle in stance and swing phases was calculated for each trial (14 values per leg).

E. Gait Features Matrix

A gait features matrix was created using the joint kinematics metrics, task error, and mean %RMS EMG values across all participants and trials. This analysis was inspired by a study from Rozumalski et al. [12], which used a k-means cluster analysis on a reduced set of gait features based on time-series kinematic data. Gait features vectors (114-length vector) were created for each trial-participant-leg combination by appending the four 20-length kinematics vectors, one 20-length task error vector, and 14 mean %RMS EMG values:

$$\begin{aligned} g_{s,t,l} = [&(\max hip_{1-20}),\ (\min knee_{1-20}), \\ &(\max knee_{1-20}),\ (\max ankle_{1-20}), \\ &(task\, error_{1-20}),\ (\%RMS\, EMG_{1-14})] \end{aligned} \quad (1)$$

where s is the participant number, t is the trial number, and l is the leg number.

All gait vectors were then vertically concatenated to form the gait features matrix:

$$G = \begin{bmatrix} g^1_{1,1,1} & \cdots & g^{114}_{1,1,1} \\ g^1_{1,2,1} & \cdots & g^{114}_{1,2,1} \\ & \vdots & \\ g^1_{22,10,2} & \cdots & g^{114}_{22,10,2} \end{bmatrix} \quad (2)$$

A total of 49 of 440 vectors were removed from the gait matrix due to issues with the EMG signals, potentially caused by EMG sensors detaching from skin during a trial or the exoskeleton cables hitting the sensors. The final gait matrix G was a 391 $\times$ 114 matrix.

F. Cluster Analysis

Principal component analysis (PCA) was performed to reduce the dimensionality of the data. The first 35 basis vectors accounted for 95% of the data's variability. Thus, the projection of the original gait matrix G onto the first 35 basis vectors, also known as the gait scores ($\tilde{G}$) were used to perform the cluster analysis, thus reducing the dimensionality by 69.3%. A k-means cluster analysis [13] was performed on $\tilde{G}$ to identify groups of gait strategies. The number of clusters was iteratively increased from 2 to 10 clusters and the Calinski-Harabasz (CH) index was calculated for each iteration. The CH index is a measure of the ratio between intra-cluster distances and inter-cluster distances [14] and was maximized to find the appropriate number of clusters.

G. User Perception of Fluency

A survey on user perception of exoskeleton system performance and task accuracy was conducted after each trial. The methodology and results are detailed by Wu et al. [15]. The question "Rate how you felt the exoskeleton supports your actions" was used to obtain a measure of user perception of human-exoskeleton fluency. The associated rating scale responses ranged from 1 (extremely hinders actions) to 5 (extremely supports actions).

H. Statistical Analysis

One-sample t-tests were performed within clusters across all metrics (kinematics, EMG, and absolute task error) with no p-value corrections ($\alpha = 0.05$). Cohen's d effect sizes (d) were calculated for all t-tests to provide context on effect size, where $0.2 < d < 0.5$ was considered small, $0.5 < d < 0.8$ was

TABLE II
JOINT KINEMATICS METRICS AND ABS. TASK ERROR ACROSS FIVE CLUSTERS

	Cluster 1 (n=59)		Cluster 2 (n=161)		Cluster 3 (n=57)		Cluster 4 (n=57)		Cluster 5 (n=57)	
Max. hip flexion @ swing (°)	1.95 (1.74)	*	0.03 (1.42)		0.75 (1.63)	*	0.33 (1.58)		-0.50 (1.68)	*
Min. knee flexion @ l.r. (°)	-1.83 (1.54)	*	-0.07 (1.07)		2.74 (1.61)	*	-0.46 (1.38)	*	-1.75 (2.05)	*
Max. knee flexion @ swing (°)	4.49 (3.07)	*	0.10 (3.06)		4.97 (3.03)	*	1.38 (2.80)	*	0.66 (2.29)	*
Max. plantarflexion (°)	0.18 (2.77)		0.23 (1.89)	*	4.81 (2.50)	*	-0.20 (3.20)		4.39 (2.42)	*
Abs. task error (mm)	116.62 (52.58)		82.42 (41.80)		108.14 (53.94)		240.62 (47.39)		87.94 (51.11)	

Notes: Joint kinematics metrics (mean (SD)) were mean-shifted by baseline values, calculated as the mean of each metric at the last 60 strides during the training session. The n-values represent the number of gait vectors sorted to each cluster (391 total). The asterisks (*) mark significant changes from baseline.

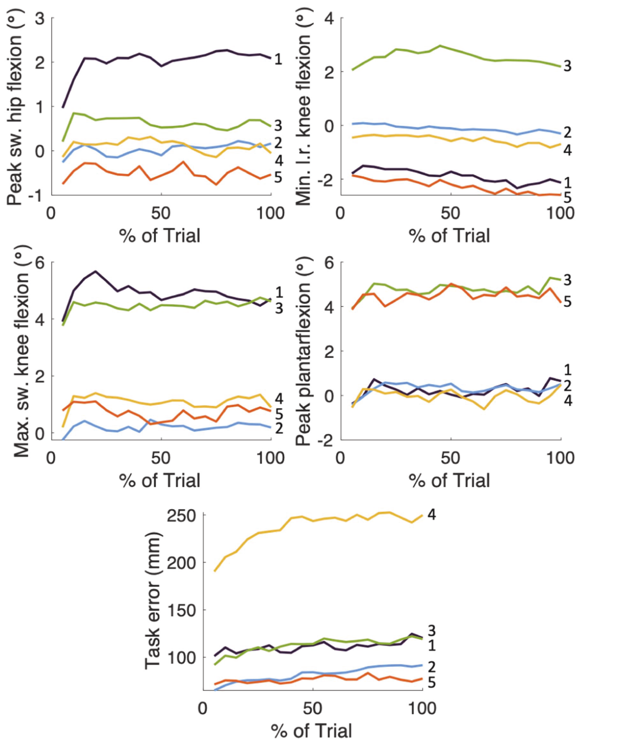

Fig. 2. Mean joint kinematics metrics and abs. task error over a trial across five clusters. Joint kinematics metrics were mean-shifted by baseline values, calculated as the mean of each metric at the last 60 strides during the training session. Cluster assignment numbers are labeled on the right of each line.

medium, and $d > 0.8$ was large. An ANOVA was performed for the survey responses on exoskeleton supportiveness with a random factor of Participant and a fixed factor of Cluster (5 levels). Post-hoc analysis involved independent t-tests across Clusters with a Bonferroni correction.

III. Results

A. Cluster Analysis

Five clusters were identified (CH index $= 59.22$) across all participant gait strategies (Figs. 2, 4). CH index values for other clustering k-values ranged from 47.98 to 57.76; thus, we selected the cluster number ($k = 5$) with the highest CH index. A t-SNE plot was created to illustrate the separation between gait strategies using the reduced gait matrix (Fig. 3). Four clusters exhibited different strategies that allowed the participant to accomplish the targeted stepping task ($\leq$160 mm error) and one cluster had increasingly poor task performance (>160 mm error) over a trial. The mean joint kinematics metrics, task error, and RMS muscle activation are summarized in Tables II and III.

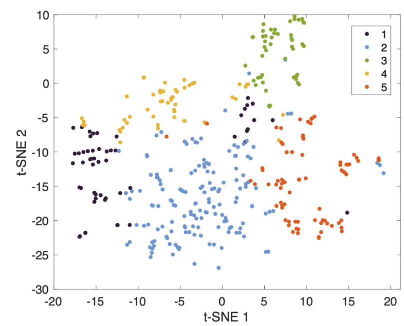

Fig. 3. A t-SNE plot of $\tilde{G}$, the gait matrix projected onto the first 35 principal components identified using PCA dimensionality reduction.

Cluster 1 significantly increased hip flexion at swing (+1.95°, $d = 1.26$) compared to baseline in order to maintain acceptable task error (116.62 mm) (Fig. 2). At swing, participants in this cluster increased RF (+33.68%, $d = 0.48$) and TFL (13.14%, $d = 0.27$) activation and decreased GMax (-9.10%, $d = 0.21$) activation, thus supporting an increase in active hip flexion at swing (Fig. 4). Participants of Cluster 1 also decreased their minimum knee flexion during loading response ($-1.83°$, $d = -1.39$) and increased knee flexion during swing (4.49°, $d = 1.58$). Participants modulated their muscle activity during stance by decreasing GAS activation (-4.25%, $d = 0.30$), which may have impacted knee flexion at loading response. Participants also increased GAS activation at swing (20.95%), which may have contributed to increased knee flexion at swing. Cluster 1 participants did not significantly change plantarflexion across a trial (0.18°, $d = 0.07$).

Cluster 2 did not significantly ($p > 0.05$) change their joint kinematics metrics (hip flexion $= 0.03°$ ($d = -0.03$), min. knee flexion at stance $= -0.07°$ ($d = -0.09$), max. knee flexion at swing $= 0.10°$ ($d = -0.04$)) and maintained acceptable task error (82.42 mm). Participants significantly increased plantarflexion (0.23°, $p < 0.001$) but with a very small effect size ($d = 0.18$). Muscle activation at stance and swing had small significant changes in most muscles ($|d| < 0.20$), with small increases in TA (12.44%, $d = 0.20$) and GAS (10.31%, $d = 0.29$) activation at stance (Fig. 4).

Cluster 3 had significant changes ($p < 0.001$) at the knee and ankle compared to baseline and had acceptable task accuracy (108.14 mm). Participants increased minimum knee flexion during loading response (+2.74°, $d = 1.84$), maximum knee flexion during swing (+4.97°, $d = 1.67$), and maximum plantarflexion (+4.81°, $d = 2.14$). The changes in knee kinematics during stance were supported by decreases in antagonistic BF activation (-11.47%, $d = 0.47$) and RF activation (-15.65%, $d = 0.29$),

TABLE III
%RMS EMG AT SWING AND STANCE PHASES ACROSS FIVE CLUSTERS

	Cluster 1 (n=59)		Cluster 2 (n=161)		Cluster 3 (n=57)		Cluster 4 (n=57)		Cluster 5 (n=57)	
TA @ stance (%)	41.66 (62.43)	*	12.44 (63.20)	*	-14.68 (38.15)	*	-24.09 (41.98)	*	37.41 (71.92)	*
GAS @ stance (%)	-4.25 (13.98)	*	10.31 (35.35)	*	-0.41 (32.61)		1.72 (9.04)		29.63 (57.64)	*
SOL @ stance (%)	-4.01 (22.74)		9.24 (51.46)	*	3.45 (56.53)		2.55 (19.34)		46.28 (111.97)	*
BF @ stance (%)	-1.94 (36.80)		-3.87 (30.05)		-11.47 (23.78)	*	2.71 (60.91)		23.60 (37.36)	*
RF @ stance (%)	-4.60 (29.89)		-9.95 (48.77)	*	-15.63 (53.28)	*	-12.04 (35.29)	*	-7.76 (44.00)	
GMax @ stance (%)	-7.78 (15.35)	*	3.14 (46.61)		-5.76 (20.28)		-7.47 (10.87)	*	23.31 (55.68)	*
TFL @ stance (%)	-6.51 (25.11)		-7.45 (38.62)	*	-27.69 (17.51)	*	-28.48 (47.34)	*	9.85 (47.08)	
TA @ swing (%)	7.01 (33.49)		8.65 (35.48)	*	42.19 (72.92)	*	30.88 (26.69)	*	20.01 (58.52)	*
GAS @ swing (%)	33.27 (68.41)	*	2.70 (52.41)		26.88 (37.13)	*	19.03 (40.78)	*	9.23 (62.22)	
SOL @ swing (%)	5.91 (56.91)		-0.54 (60.21)		44.53 (71.97)	*	-8.93 (45.10)		-24.16 (41.68)	*
BF @ swing (%)	2.89 (42.88)		12.13 (59.04)	*	84.10 (72.03)	*	12.00 (44.60)		-8.45 (29.99)	*
RF @ swing (%)	33.68 (50.23)	*	6.76 (45.84)		11.47 (23.24)	*	16.25 (57.68)	*	9.76 (36.21)	*
GMax @ swing (%)	9.10 (42.40)		3.82 (57.70)		19.39 (20.28)	*	26.46 (41.22)	*	19.11 (56.46)	*
TFL @ swing (%)	13.14 (47.41)	*	5.07 (69.11)		98.04 (98.46)	*	2.31 (46.13)		2.90 (41.51)	

Notes: %RMS EMG metrics (mean (SD)) were mean-shifted by baseline values, calculated as the mean of each metric at the last 60 strides during the training session, then divided by the baseline values. The %RMS EMG metrics were calculated during the stance phase (top half) and swing phases (bottom half). The n-values represent the number of gait vectors sorted to each cluster (391 total). The asterisks (*) mark significant changes from baseline.

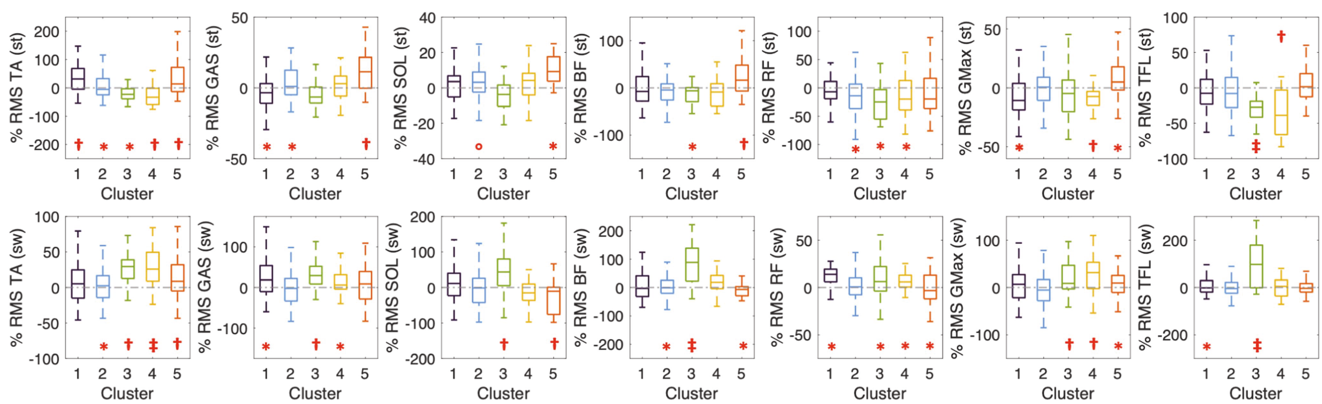

Fig. 4. Boxplots of %RMS EMG of muscle activation during stance (top row) and swing (bottom row) phases across five clusters. %RMS EMG metrics were mean-shifted by baseline values, calculated as the mean of each metric at the last 60 strides during the training session, then divided by the baseline values. Each box includes 25th to 75th percentile and whisker length is 1.5*IQR. Significant changes in %RMS EMG compared to baseline are marked with red symbols, where ∘ represent very small effect sizes ($|d| < 0.2$), $*$ are small ($0.2 < |d| < 0.5$), † are medium ($0.5 < |d| < 0.8$), and ‡ are large ($|d| > 0.8$).

creating a positive knee flexion moment between antagonistic muscles (Fig. 4). Increases in knee flexion at swing corresponded to increases to BF (84.10%, $d = 1.15$) and GAS (26.88%, $d = 0.71$) activation at swing. The increase in plantarflexion were linked to increased GAS (26.88%, $d = 0.71$) and SOL (44.53%, $d = 0.61$) activation during swing. Participants in Cluster 3 also moderately increased hip flexion (0.75°, $d = 0.50$), driven by a large increase in TFL activation at swing (98.04%, $d = 0.98$) and reduced by an antagonistic increase in BF activity (84.10%, $d = 1.15$).

Cluster 4 had mostly unchanged ($p > 0.05$) joint kinematics metrics (hip flexion = 0.33° ($d = 0.23$), plantarflexion = $-0.20°$, $d = 0.07$), with a small decrease in minimum knee flexion at loading response ($-0.46°$, $p = 0.01$, $d = 0.35$), a moderate increase in maximum knee flexion at swing (+1.38°, $p < 0.001$, $d = 0.52$), and unacceptable task error (240.62 mm). Participants increased GAS activation at swing (19.03%, $d = 0.46$), which may have contributed to the increase in knee flexion at swing (Fig. 4). TA activation at swing also increased by 30.88% ($d = 1.14$), thus counteracting additional plantarflexion. Other muscles had small to moderate changes in activation (-28.48 to 24.09%, $-0.57 \leq d \leq 0.63$), with the no net change due to antagonistic muscle activity.

Cluster 5 primarily increased ankle plantarflexion (+4.48°, $d = 2.42$) and decreased minimum knee flexion at loading response (-2.26°, $d = 0.88$), with small changes to hip flexion ($-0.50°$, $d = 0.33$) and maximum knee flexion at swing (+0.72°, $d = 0.31$). Participants also had acceptable task performance across the trial (76.32 mm). The increase in plantarflexion may have been driven by increases in GAS (29.63%, $d = 0.51$) and SOL (46.28%, $d = 0.41$) activation at stance, as well as a small increase in GAS (9.23%, $d = 0.15$) swing (Fig. 4). Antagonistic TA muscle activation also increased at stance (37.41%, $d = 0.51$) and swing (20.01%, $d = 0.34$). Notably, GMax activation at swing increased by 23.31% ($d = 0.41$) with minimal change in hip flexion, as antagonistic TFL activation increased by 9.85% ($d = 0.21$).

B. Gait Strategies Across Trials

Cluster assignments for gait vectors were then sorted according to the participant number, group, trial number, and leg (Fig. 5). Group 1 trial strategies were most often sorted into Cluster 2 (108/201 trials), then to Cluster 4 (37/201 trials), Cluster 1 (34/201 trials), Cluster 3 (14/201 trials), and Cluster 5 (8/201 trials). Nine (81.8%) participants in Group 1 used

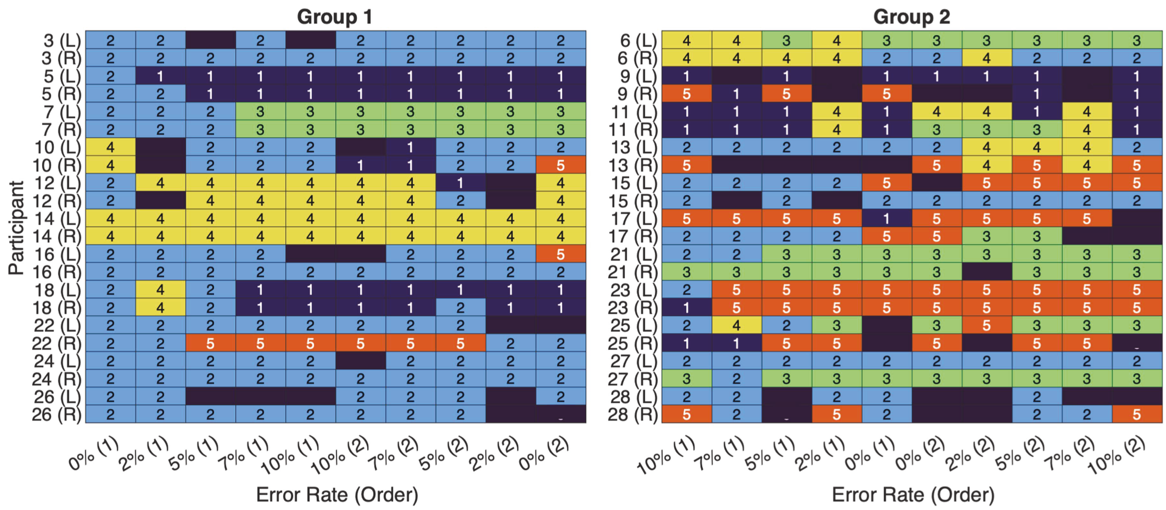

Fig. 5. Cluster assignments for all participants and trials. 49 trials were excluded from analysis due to noisy or unusable EMG data and are marked using unlabeled black boxes. Participant number and leg (left or right) are marked on the left of each cluster map. Trial error rates and order (1st or 2nd exposure to the error rate) are shown on the x-axis.

strategies defined in Cluster 2 in the first trial and six (54.5%) of those participants changed strategies as they experienced different exoskeleton controllers with varying error rates. Two (18.2%) participants primarily used the Cluster 4 strategy and did not successfully complete the stepping task across trials.

Group 2 trial strategies were sorted into the clusters with the following frequencies: Cluster 2 (53/190 trials), Cluster 5 (49/190 trials), Cluster 3 (43/190 trials), Cluster 1 (25/190 trials), and Cluster 4 (20/190 trials). All 11 participants in Group 2 used strategies of various clusters when experiencing different controllers.

C. User Perception of Fluency

The Subject factor ($F(21, 388) = 23.61, p < 0.001$) and Cluster factor ($F(4, 388) = 2.66, p = 0.033$) were significant for perceived exoskeleton supportiveness. Perceived supportiveness in Cluster 2 (3.51 ± 0.90) was significantly higher than in Cluster 3 (3.06 ± 1.09). Responses in Clusters 1 (3.78 ± 0.98), 4 (3.84 ± 1.38), and 5 (3.71 ± 0.94) were not significantly different compared to Cluster 2.

IV. Discussion

In this study, we introduced an exoskeleton algorithm with varying error rates (0%, 2%, 5%, 7%, and 10% error) to observe the effect of exoskeleton error levels on gait strategies during nominal operation periods. Participants were sorted into two groups that experienced each controller twice, but in different orders. A k-means clustering algorithm ($k = 5$) was used to define gait strategies across participants using metrics of joint kinematics, task error, and muscle activity. These clusters of strategies were then interpreted in the context of human-exoskeleton fluency.

A. Interpretation of Clusters

Gait strategies defined by the cluster analysis had varying impacts on human-exoskeleton fluency, which was maximized when users reduced muscle activity as the goal of the Dephy exoskeleton is to reduce the metabolic cost of walking. Muscle activity was used to assess strategies as it has been shown to be linked to metabolic cost during walking [16]. Fluent strategies may involve minimal changes or decreases in muscle activity with respect to participants' initial adaptation to the exoskeleton at the end of training. Cluster 2 exhibited strategies that supported human-exoskeleton fluency while successfully completing the stepping task, even when errors were present throughout a trial. Participants in Cluster 2 were able to coordinate with the exoskeleton and utilize the exoskeleton's assistive torque during nominal steps to complete the task without significant modifications to joint kinematics and muscle activity (Tables II and III). While participants in Cluster 4 were also fluent with the exoskeleton, they were unable to achieve acceptable task error ($\leq$160 mm), suggesting that users may have directed less attention to the task or were unable to match the treadmill speed and may have altered walking speed if they had been on a self-paced treadmill or were overground.

In comparison, Clusters 1, 3, and 5 increased muscle activation and modified joint kinematics about the hip (Cluster 1), knee (Clusters 3 and 5), and ankle (Clusters 3 and 5) in order to complete the task with acceptable error (Figs. 2 and 4). Cluster 1 utilized a strategy observed in our previous study with a 2% error algorithm [6], where participants increased hip flexion and muscle activity about the hip to extend the leg and reach the stepping target during exoskeleton errors. This strategy was previously only observed during exoskeleton errors and participants were able to return to baseline behavior after errors. In this study, participants increased hip flexion and muscle activity even during nominal exoskeleton behavior, indicating that users may have expected the presence of errors and modified their strategies to accomplish the stepping task. Similarly, Clusters 3 and 5 may have increased plantarflexion and muscle activation about the ankle in anticipation of additional exoskeleton errors. The added plantarflexion may have generated a larger push-off force, which then followed with increased muscle activation and co-contraction in the hip and knee, possibly to stiffen the joints and prevent over-stepping the target. The strategies used by Clusters 1, 3, and 5 negatively impacted human-exoskeleton fluency as participants increased joint flexion and muscle activity, which increased energy usage and thus opposed the design goals of this exoskeleton. These strategies may also indicate that users in these clusters may have prioritized task performance over fluent gait strategies and lost trust in the exoskeleton to actuate correctly over time. Participants in Cluster 3 also perceived the exoskeleton as less supportive than those in Cluster 2, which may be linked to non-fluent strategies in Cluster 3. While participants in Clusters 1 and 5 also utilized non-fluent strategies, the increases in muscle activation supporting hip flexion and ankle plantarflexion occurred during stance. The increased muscle activation across all muscles during swing observed in Cluster 3 may be more salient, leading to lower supportiveness ratings.

B. Gait Strategies Across Trials

Most participants (18 of 22, 81.8%) changed gait strategies as they experienced additional the exoskeleton algorithm with different error levels (Fig. 5). In Group 1, participants often began with gait strategies defined in Cluster 2 that were fluent with the exoskeleton's goals and accomplished the stepping task. Six participants (54.5%) were able to maintain fluent gait strategies (Cluster 2) on one or both legs during all trials. These participants may have trusted the exoskeleton to continue to support their actions, even when walking with algorithms with higher error frequencies. These six participants stated that they primarily focused on completing the stepping task and tried to coordinate with the exoskeleton's behavior, regardless of error rate. Three participants (27.3%) transitioned to strategies that increased hip or ankle flexion and muscle activity in order to maintain task accuracy (Clusters 1, 3, and 5), thus reducing human-exoskeleton fluency. These users may have lost trust in the exoskeleton once they encountered controllers with higher error, as they continued with these compensatory strategies when walking with 0% or 2% error controllers. The contrast between participant behavior within Group 1 may indicate that some users may be more heavily impacted by poor algorithm performance than others.

In Group 2, all participants changed strategies across trials and were more likely to increase hip and ankle flexion and underlying muscle activity (50% of strategies) than to utilize strategies that supported human-exoskeleton fluency (27.9% of strategies). Group 2 participants were also more likely to start with non-fluent strategies on at least one leg (90.9%) compared to Group 1 participants (18.2%). This behavior aligns with the order presented, as Group 2 began with the lower performing algorithm (10% error) after training, while Group 1 began with the algorithm with no errors, thereby impacting the strategies used during the first trial. However, when Group 2 participants transitioned to algorithms with lower error (0% or 2%) in later trials, most participants (90.9%) maintained increases in hip or ankle flexion as defined in Clusters 1, 3, and 5. This behavior is similar to users in Group 1 who were strongly impacted by poor controllers and modified their gait strategies for the remaining trials. These users may have updated their underlying internal models—representations of the dynamic properties of the limb in the environment [7]—when walking with an exoskeleton, leading to changes in walking strategies. Adaptation of internal models may occur in response to visual [8] or mechanical changes in the environment [10], which cause errors in movement. Algorithms with a higher frequency of movement errors may influence the dynamics within coupled human-exoskeleton system, thus prompting modifications of internal models and the resulting motor commands.

Participants who experience poor controllers earlier or are sensitive to exoskeleton errors were more likely to use gait strategies with increased muscle activity and joint flexion, thereby conflicting with the exoskeleton's goal. Users should first adapt to and use exoskeletons in settings where error frequency is low for an ample amount of time (i.e., steady-state walking in laboratory) before walking in more uncertain environments where errors may be more prevalent (i.e., uneven terrain, ramps, speed-variable walking) to build sufficient experience and trust in the exoskeleton. In this study, participants walked for 15 minutes with a 0% error controller at a fixed speed during the training session, which may have been too short and uniform for some participants to explore different speeds and develop a resilient and fluent gait strategy. Participants in Group 1 began to utilize less fluent walking strategies once algorithm errors increased to 5–7% of all strides. Participants who started with 10% error were less likely to exhibit fluent strategies throughout the experiment. Thus, it is recommended that researchers strive to have systems with errors below 5–7% error. We acknowledge that this threshold may be larger if error types were less noticeable compared to this study or may be lower if gait stability or foot clearance were affected (i.e., early/late actuations).

It is currently unclear how long a system must operate correctly after a period of errors for the user to transition to more fluent strategies. A study involving the same Dephy exoskeleton found that some participants maintained a stepping strategy developed when adapting to the exoskeleton even when the exoskeleton was turned off for 5 minutes [17]. This finding suggests that some users may need at least 5 minutes of walking without exoskeleton errors before modifying their gait strategies. Due to time limitations of the study, none of the controllers other than 0% error had a period greater than 5 minutes without errors as each trial lasted between 10–15 minutes. It is also important to evaluate the impact of lower-limb exoskeletons on the entire kinematic chain of the leg rather on one specific joint, as the data shows increased muscle activity and modified kinematics about the hip and knee while walking with an ankle exoskeleton.

C. Limitations and Future Work

This study supports that users may utilize various gait strategies when given a targeted stepping task with a powered ankle exoskeleton in the presence of errors. Fluent strategies minimize changes in joint kinematics and muscle activity during nominal exoskeleton behavior. Users may increase hip or ankle flexion to support completing the task, thus negatively impacting human-exoskeleton fluency. A limitation of this study is the assumption that participants were fully adapted to the exoskeleton's normal operation within 15 minutes of training, which would impact our calculation of baseline joint kinematics and muscle activation. Clusters defined in this study did not show large decreases in GAS or SOL activation (an indication of post-training adaptation), though individual users may have continued to adapt to the system after training. A study estimated that users may need up to 109 minutes to fully adapt to a different ankle exoskeleton [18], which was not feasible for the duration of this study.

While this study introduced error rates in two fixed orders, randomized error rates may result in different user responses. For instance, if the randomized order began with a higher error, the user may increase muscle activation as they anticipate repeated errors (non-fluent strategy), even if the following controller had a low error rate. Future work may explore how the order of error rates may affect learning and adaptation to an exoskeleton to inform training protocols and operational use. Alternate exoskeletons and error types (i.e., changes in different control parameters) may also yield different responses across error ranges. Future work may explore new algorithms that modulate exoskeleton behavior in response to gait strategies that reduce human-exoskeleton fluency.

V. Conclusion

In this study, we investigated the impact of imperfect exoskeleton algorithms (up to 10% error) on joint kinematics, muscle activation, and task error. Error rates were presented in two orders–Group 1 experienced controllers with low error (0–2%) before those with higher error rates (5–10%) and Group 2 experienced controllers with higher error before those with lower error rates. A k-means cluster analysis ($k = 5$) was used to define the emergent gait strategies. The fluent strategy minimized muscle activation and aligned with the exoskeleton's goal of reducing metabolic cost while maintaining acceptable task error. Three strategies had acceptable task error, but increased muscle activation about the hip or ankle, thus negatively impacting human-exoskeleton fluency. One strategy minimized muscle activity, but had unacceptable task performance. Participants in Group 2 who experienced 10% error first were more likely to use non-fluent gait strategies compared to those who walked with 0% error first. A subset of users across both groups transitioned from fluent to non-fluent gait strategies after using the controller with higher error rates. Exoskeleton users may build fluent and resilient gait strategies if they first walk with the exoskeleton in environments with low variability (i.e., treadmill walking) before transitioning to more uncertain environments where exoskeleton errors may be more prevalent. Understanding emergent gait strategies can inform the development of exoskeleton algorithms that support appropriate gait strategies and system use.

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