Improving Complex Task Performance in Powered Upper Limb Exoskeletons With Adaptive Proportional Myoelectric Control for User Motor Strategy Tracking

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***Abstract*—Powered exoskeletons have emerged as promising tools with applications in assistance, augmentation, and rehabilitation. However, the realization of their full potential hinges on the accurate classifications of user intent. Traditional proportional myoelectric controllers with fixed thresholds require users to develop the necessary motor program – the optimal coordination of movements with the exoskeleton – prior to effective operation. Novices, who may not have mastered this coordination, often experience decreased accuracy in intention classification, leading to a trade-off between ease of static and dynamic tasks: easier movement initiation typically results in less stable holding, and vice versa. This study introduced a novel proportional myoelectric controller with real-time adaptive thresholds designed to continuously track the user's evolving motor program to enhance intent classification for both movement and holding. In an elbow target position matching task with twelve participants, this controller showed reductions in both intention classification error magnitudes and muscular effort during movement initiation compared to the traditional fixed thresholds method. Nonetheless, participants did not perceive significant improvements, suggesting the need for continued enhancements. This letter presents an innovative approach to leveraging the user's current motor program for determining intention classification parameters, moving beyond the limitations of fixed or manually-tuned settings.**

***Index Terms*—Prosthetics and exoskeletons, wearable robotics.**

I. Introduction

POWERED exoskeletons are designed to assist human movement, showing potential in assisting the elderly or people with disability in daily activities, augmenting able-bodied individuals in labor-intensive tasks, and restoring motor function in patients [1]. A critical element in the development of these exoskeletons is designing controllers that can understand user intentions for timely assistance. However, most controllers are pre-calibrated and remain unchanged once optimized [2], [3], [4], often failing to account for the user's changing behaviors due to motor learning or fatigue.

Continuous adaptation is pivotal in human-robot collaboration to ensure optimal team performance over time. Extensive research in human-manipulator collaboration has focused on this adaptation [5], [6], [7]. In these scenarios, robots are designed to lead physical tasks under human supervision, while also being compliant to human intervention. These tasks often require repetition or predefined trajectories/states for the robot to learn and execute. Similarly, adaptive strategies are explored in human-exoskeleton collaboration that support repetitive and predefined trajectories. For example, an exoskeleton can learn a specific task and eventually take full control, compensating for the human effort with robotic assistance (e.g., elbow exoskeleton [8]). Another strategy involves the exoskeleton coordinating with the user's movements to optimize the torque profile for certain repetitive tasks, such as walking (e.g., ankle exoskeleton [9]). Rather than learn the motion or torque profile, exoskeletons can continuously adapt the initiation of predefined states (e.g., thumb exoskeleton [10]).

However, in daily activities, movements are often not repetitive and lack predefined patterns, particularly with upper body motions. Therefore, upper-extremity exoskeletons often use electromyography (EMG) signals to predict instant user intentions, focusing on estimating and delivering the desired torque at each subsequent time point. EMG signals, which precede muscle contractions by 20 to 80 milliseconds [11], offer a more immediate reflection of human intention compared to kinematic-based approaches [12], leading many EMG-based methods to prioritize enhancing this estimation [13], [14]. However, it is arguable whether such high accuracy is necessary for effective assistance. Proportional myoelectric control, which converts muscle signals directly into exoskeleton actuator inputs, depends on the human central nervous system to compensate for its less precise torque estimation [15], [16], [17]. This approach assumes a fixed relationship between muscle and movement patterns, aligning the exoskeleton's response with the muscle pattern and

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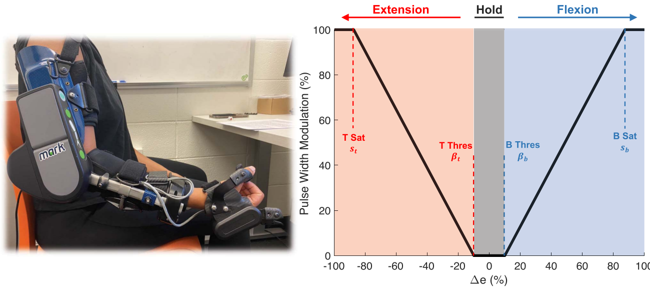


Fig. 1. Left: Overview of a participant wearing the Myomo exoskeleton during the experimental session. Right: The control scheme of Fixed Controller. $\Delta e(\%)$ = biceps EMG effort - triceps EMG effort.

thereby reflecting the user's movement intention. However, the correlation between muscle activity and movement intention can vary under different conditions. For instance, when flexing the elbow against gravity, biceps contraction might aim to maintain position rather than initiate flexion [18].

Furthermore, complex tasks that combine dynamic and static components present additional challenges in controller parameter selection: optimizing performance for one type of task often risks impairing another. For example, in our work with an elbow exoskeleton capable of holding, flexion, and extension, we found that while lower thresholds facilitate movement initiation, they may reduce stability during position holding due to unintended movements triggered by small muscle activations [15]. This finding underscores the need for precise threshold tuning, which should ideally be aligned with the user's current motor strategy, to ensure accurate exoskeleton responses to intended movements. Moreover, as novice users adapt to exoskeletons or as experienced users encounter fatigue, their changing behaviors call for continuous adjustments in control parameters for sustained optimal assistance over time [9]. Hence, there is a need for a continuously adaptive exoskeleton controller capable of effectively managing complex movements.

In this study, we introduced an adaptive proportional myoelectric controller for an active elbow exoskeleton designed to track the user's current motor strategy and utilize it to set real-time thresholds, enabling personalized and optimal parameter adjustments over time. This approach could mitigate the trade-off between dynamic and static tasks in exoskeleton usage. We evaluated its performance through a target position matching task. We hypothesized that the adaptive controller would outperform the fixed controller in accurately classifying user intentions and reducing movement initiation efforts, thereby enhancing participant perceptions.

II. Exoskeleton and Control Methods

A. Exoskeleton Hardware

Participants wore a portable right-arm EMG-based upper limb exoskeleton (Model: Mark, Myomo, Inc., Boston, MA) (Fig. 1: Left). The experimenter assisted in positioning non-invasive EMG sensors on the biceps brachii and triceps brachii (long head) according to the SENIAM standards [19]. The EMG signals (sampling rate: 1 kHz) were smoothed using a 4th order bandpass filter from 100 to 200 Hz, followed by rectification and then processed using a Kalman filter. The exoskeleton state variables (*e.g.*, filtered EMGs, elbow motor angle) were transmitted to a laptop via a serial cable (data streaming rate: 20 Hz). Detailed descriptions of the exoskeleton and its embedded device modes are provided in [15].

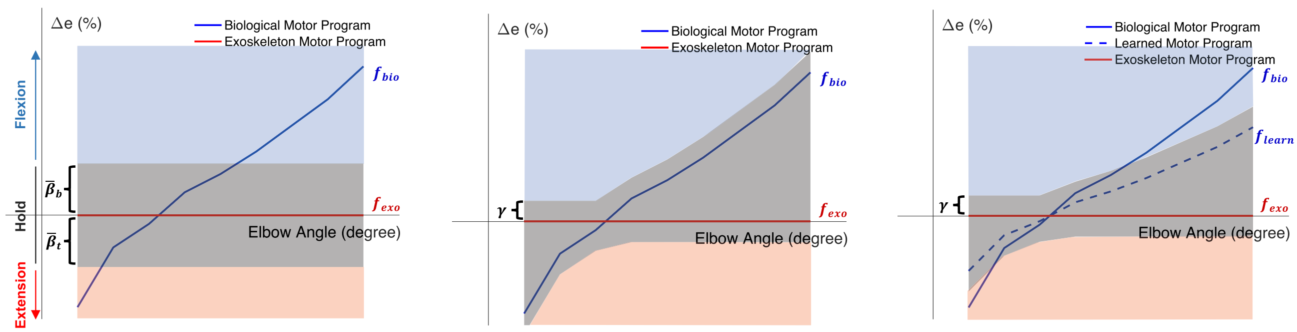
B. Fixed Controller

The conventional proportional myoelectric controller generates assistive torques proportional to the EMG from the primary muscles involved in the movement, aligning with their agonist-antagonist roles [16], [17]. The embedded controller of the Myomo exoskeleton (*Fixed Controller*) follows a similar principle. It first amplifies the recorded muscle signals using a biceps gain (k_b) and triceps gain (k_t). These amplified signals are then scaled according to a gain specified by the manufacturer, set at 75 for both muscles. The resultant EMG effort (e) is standardized to range between 0 and 100, truncating values exceeding 100. The difference between biceps and triceps EMG efforts (Δe) is directly proportional to the percentage of Pulse Width Modulation (PWM) (Fig. 1: Right), which in turn relates to the elbow motor's speed ($\dot{\theta}$) under no load. Biceps and triceps thresholds (β) are set to enable the classification of holding intention. If Δe remains within the biceps and triceps thresholds (grey area), the elbow motor speed $\dot{\theta}$ stays constant at 0, and a PID controller is active to maintain the position. Outside this deadzone, the control signal is proportional to Δe until reaching the maximum PWM value, beyond which it is maintained at 100 once Δe surpasses the saturation level (s).

The selection of β in the Fixed Controller can vary, with selection dependent on user preference or the experience of device specialists. In practice, this selection results in a trade-off: expanding the holding region (grey area) leads to a reduction in the movement region (red and blue areas). Consequently, larger thresholds enhance stability during position holding but make movement initiation more effortful.

To effectively use the exoskeleton, users need to develop an appropriate motor program, defined as a pre-structured neural pattern coordinating muscle contractions for specific movements. When interacting with an exoskeleton, users need to develop what we term an *Exoskeleton Motor Program (Exoskeleton MP, f_{exo})*, which differs from the *Biological Motor Program (Biological MP, f_{bio})* typically used in daily activities without exoskeletons. For example, a nominal *Biological MP* requires individuals to contract their biceps to maintain their arms at a flexed elbow angle in the body's sagittal plane, counteracting gravity's influence (Fig. 2(a)). However, with exoskeleton support, such muscle contractions can become unnecessary. For the Fixed Controller, users should fully relax their muscles when holding a flexed posture to align with the controller's design. The *Biological MP* can be characterized by an increasing Δe (difference between biceps and triceps EMGs) as the elbow angle increases, whereas the *Exoskeleton MP* allows users to rely entirely on the exoskeleton for maintaining position, resulting in no muscle activation regardless of elbow angle:

$$\text{Exoskeleton MP}: \quad f_{exo}(\theta_{elbow}) = 0 \tag{1}$$



(a) Fixed Controller (b) Adaptive Controller (c) Real-time Adaptive Controller

Fig. 2. (a) *Fixed Controller:* Thresholds in this controller are based on the *Exoskeleton MP* and remain fixed once set. Participants adopting the *Biological MP* could struggle to maintain positions at flexed elbow angles because of their contracting muscles habitually. (b) *Adaptive Controller:* The holding region in this controller is delineated using both the *Biological MP* and the *Exoskeleton MP*. The threshold values β are now a function of the elbow angle θ_{elbow}. γ is introduced to compensate for EMG signal variations. (c) *Real-time Adaptive Controller:* The holding region is delineated using the *Learned MP* instead of the *Biological MP*. It dynamically and in real-time tracks the user's evolving motor program as they learn and adapt to the exoskeleton.

The Fixed Controller assumes the user adopts the *Exoskeleton MP* and uses (2) to set thresholds β:

$$\text{Fixed Controller:} \quad \begin{cases} \beta_b = f_{exo}(\theta_{elbow}) + \bar{\beta}_b = \bar{\beta}_b \\ \beta_t = f_{exo}(\theta_{elbow}) - \bar{\beta}_t = -\bar{\beta}_t \end{cases} \tag{2}$$

$\bar{\beta}_b$ and $\bar{\beta}_t$ are typically chosen to balance movement facilitation with holding stability, as previously discussed. Moreover, setting larger values for $\bar{\beta}_b$ and $\bar{\beta}_t$ incorporates a greater portion of the *Biological MP* within the holding region, allowing users, especially novices who predominantly use the *Biological MP* to maintain their position across a wider range of elbow angles. However, it also introduces a challenge in initiating movement, as users must overcome a higher threshold, particularly at low elbow angles.

C. Adaptive Thresholds Proportional Myoelectric Controller

An ideal controller should incorporate the *Biological MP* while also maximizing the movement region. The *Adaptive Controller* uses both the *Biological MP* and the *Exoskeleton MP* as classification boundaries (Fig. 2(b)). The threshold values β are adjusted based on the elbow angle, ensuring a more accurate classification between movement and holding.

As users gradually learn and adapt to exoskeletons, they often transition through an intermediate phase between the *Biological MP* and the *Exoskeleton MP*. In this phase, users partially rely on the exoskeleton while also exerting personal effort to maintain positions. This intermediate stage is common during exoskeleton adaptation, as complete adaptation often requires an extended period [20]. We term this intermediate phase the *Learned Motor Program (Learned MP, f_{learn})*. An ideal controller (*Real-time Adaptive Controller*) should have the capability to track the user's *Learned MP* in real time to adjust the classification boundary from the *Biological MP* (Fig. 2(c)):

Real-time Adaptive Controller:

$$\begin{cases} \beta_b(\theta_{elbow}) = \max\{f_{exo}(\theta_{elbow}), f_{learn}(\theta_{elbow})\} + \gamma \\ \beta_t(\theta_{elbow}) = \min\{f_{exo}(\theta_{elbow}), f_{learn}(\theta_{elbow})\} - \gamma \end{cases} \tag{3}$$

γ is added to compensate for EMG signal variations. For expert users, whose *Learned MP* is expected to closely align with the *Exoskeleton MP*, the Real-time Adaptive Controller should have configurations similar to the Fixed Controller.

Algorithm 1: $(\beta_b, \beta_t) \leftarrow Adaptive\,Controller\,(\theta_{elbow}, e_b, e_t)$.

```
λ = [0, 0]; τ = False;
for t = 0 to t = t_end do
  θ⃗_hold, e⃗_b, e⃗_t ← Insert(θ_elbow, e_b, e_t)
  for len(θ⃗_hold) > N_hold then
    θ⃗_hold, e⃗_b, e⃗_t ← Pop(θ⃗_hold, e⃗_b, e⃗_t);
  end if
  if range(θ⃗_hold) < δ_angle and range(e⃗_b) < δ_biceps
  and range(e⃗_t) < δ_triceps then
    τ = True
  end if
  if τ == True then
    e⃗_ave, θ⃗_ave ←
    Insert(mean(e⃗_b − e⃗_t), mean(θ⃗_hold));
    if len(θ⃗_ave) > N_ave then
      e⃗_ave, θ⃗_ave ← Pop(e⃗_ave, θ⃗_ave))
    end if
    if len(θ⃗_ave) > N_fit and range(θ⃗_ave) > T_fit then
      λ = polyfit(θ⃗_ave, e⃗_ave, 1);
    end if
    θ⃗_hold, e⃗_b, e⃗_t ← Clear(θ⃗_hold, e⃗_b, e⃗_t);
    τ = False;
  end if
  f_learn(θ_elbow) = polyval(λ, θ_elbow);
  β_b = β_b(θ_elbow); β_t = β_t(θ_elbow)        ▷ (3)
end for
```

* $N_{hold} = 15$; $N_{ave} = 20$; $N_{fit} = 12$; $T_{fit} = 20°$.
* $\delta_{angle} = 2°$; $\delta_{biceps} = \delta_{triceps} = 5$.
* These threshold values were selected based on pilot tests.

The *Learned MP* represents a motor program that continuously evolves as users adapt to the exoskeleton. To capture this *Learned MP*, we modeled it using a first-order relationship with the elbow angle θ_{elbow}. This modeling approach was chosen for

TABLE I
PARTICIPANT ANTHROPOMETRIC MEASUREMENTS

Participant	Mean	Std	Min	Max
Age (years)	24.8	5.3	18	35
Mass (kg)	72.9	17.6	52	104.3
Height (cm)	170.3	12.8	153.5	191.6
Shoulder-Elbow Length (cm)	35.2	4.0	27.6	40.7
Forearm-Hand Length (cm)	46.2	4.0	40.5	54.5
Biceps Circumference (cm)	33.6	7.3	26.0	54.0
Forearm Circumference (cm)	27.6	2.8	24.0	33.0

its simplicity, and it was supported by the observation of an approximately linear relationship in the *Biological MP* during pilot testing. We performed real-time evaluations of the muscle and elbow angle data to continuously update this relationship. It is important to note that the *Learned MP* reflects the motor program users applied while attempting to hold their position. Therefore, only data captured during stable position maintenance (i.e., no significant changes in elbow angle: $range(\vec{\theta}_{hold}) < \delta_{angle}$, Algorithm 1, line 7) were relevant for updating the *Learned MP*. However, stable elbow angles do not always indicate an intention to maintain position. Users might actively contract their muscles in an attempt to initiate movement. If this initiation activation is insufficient, the exoskeleton may still show a stable elbow angle despite the user's intent to move. To address this case, we introduced a second criterion: consistent muscle effort should be observed (i.e., minimal fluctuations in biceps and triceps efforts: $range(\vec{e}_b) < \delta_{biceps}$, $range(\vec{e}_t) < \delta_{triceps}$, Algorithm 1, line 7).

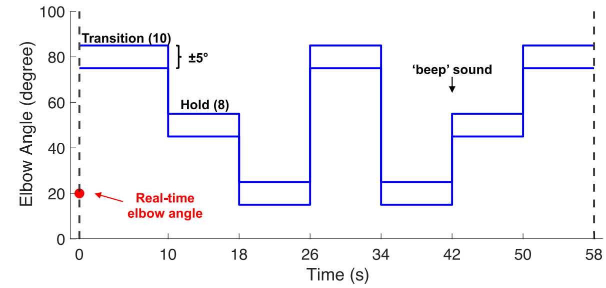
The Real-time Adaptive Controller used a sliding window of approximately 0.8 seconds, corresponding to N_{hold} data points, to scan for periods that met the aforementioned criterion (Algorithm 1, lines 3–9). The data within the sliding window were stored in $\vec{\theta}_{hold}$, $\vec{e}_b$, and $\vec{e}_t$, representing the elbow angle, biceps effort, and triceps effort, respectively. Once a satisfactory window was identified ($\tau =$ True), the average values of that specific period were calculated and stored in $\vec{e}_{ave}$ and $\vec{\theta}_{ave}$, representing the average values of recent satisfactory window periods (Algorithm 1, lines 11-14). Only the most recent N_{ave} data points were retained, as older data might not accurately reflect the user's current motor strategy. When the controller accumulated over N_{fit} data points in $\vec{e}_{ave}$ and $\vec{\theta}_{ave}$, and the range of $\vec{\theta}_{ave}$ exceeded T_{fit}, a linear mapping λ was fitted to update the *Learned MP* (Algorithm 1, lines 15-17). These criteria were used to avoid poor model fitting with limited or clustered data points (Fig. 3(b)).

The Real-time Adaptive Controller was run in Python (version 3.10.6) and communicated updated β_b and β_t values to the exoskeleton via Bluetooth.

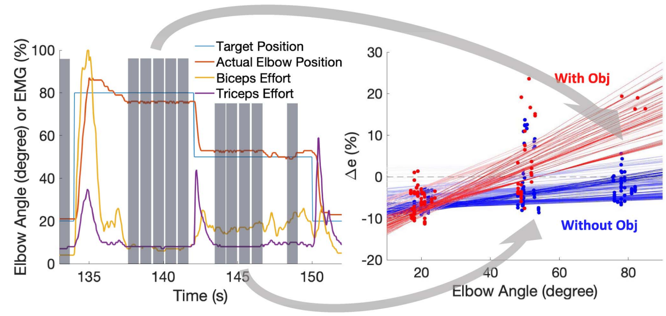
III. EXPERIMENTAL METHODS

A. Participants

Fourteen participants were recruited for this study, and twelve completed it ($n = 12$; 6F, 6 M). The anthropometric data of the participants are detailed in Table I. All participants were in good health, with no arm mobility limitations or arm injuries in the past 6 months. They were all right-handed and had no prior experience with upper-extremity exoskeletons. Written informed consent was obtained from all participants, and the study was approved by the University of Michigan Institutional Review Board (HUM00213716).



(a) Target-Matching Task



(b) Data Extraction and *Learned MP* Update

Fig. 3. (a) Sample set from the target matching task, where participants matched their elbow angle (red dot) to the target position (blue region). (b) Example illustrating the real-time extraction of data points that meet the specified criteria (in grey bins). The average elbow angle and Δe for each grey bin were used to update the *Learned MP*.

Two participants' data were excluded from the analysis. Both of them struggled in operating the exoskeleton during training and had incomplete datasets. One participant was unable to complete the study within the allotted time, while the other managed to complete more tasks; however, missing data occurred due to a data communication issue. As a result, the analysis included datasets from a total of 12 participants.

B. Experimental Protocol

The experimental protocol was adapted from Peng and Stirling [15]. A familiarization process was conducted to ensure participants' comfort and familiarity with the device. During this process, the Fixed Controller was used, with the following controller settings: $k_b = 10$, $k_t = 10$, $\beta_b = 20\%$, $\beta_k = -20\%$, $s_b = \beta_b + 74\%$, $s_k = \beta_k - 74\%$.

Participants completed a 4-module target matching task, where their goal was to align their elbow angle with a target displayed on a monitor (Fig. 3(a)). Their current elbow angle was represented by a red dot on the screen, and they were instructed to maintain this dot within the bounds of two blue lines (±5 degrees). At the start of each movement, signaled by a vertical blue line and a beep sound, participants were directed to move to a new target position. Each module consisted of 10 sets, alternating between 'With Obj' sets (holding a 2 lb dumbbell) and 'Without Obj' sets (without any additional object). In each set, three pre-selected elbow angles (20°, 50°, 80°) were held twice for 8 seconds each time. A 10-second transition period was provided at the beginning of each set. Participants were instructed to:

- Track the target as quickly and accurately as possible.
- Minimize muscle effort throughout the experiment.

Half of the participants began the experiment using the Fixed Controller, while the remaining half started with the Real-time Adaptive Controller. At the 3 rd module, they switched to the alternate controller. The assignment of participants to the controllers was randomized but included a process to ensure balanced order sizes and equal gender representation in each order. Each module lasted about 10 minutes, with 3-minute intervals between modules. After the 2nd and 4th modules, participants provided their perceptions of each controller's performance through a survey (Table IV).

The initial settings for the Fixed Controller were identical to those used during the familiarization phase. For the Real-time Adaptive Controller, we set $\gamma = 5\%$, with other related parameter values unchanged. The controller imposed constraints on the thresholds: $-65\% \leq \beta_t \leq -10\%$ and $10\% \leq \beta_b \leq 65\%$, which were defined by embedded manufacturer software bounds. If any threshold value fell outside of these ranges, it would be adjusted to the nearest allowable value. Algorithm 1 was executed separately for sets where participants were holding objects and those where they were not.

C. Data Analysis

The collected data were analyzed in MATLAB (MathWorks, Natick, MA, USA). We proposed two metrics to evaluate the performance of the controllers: intention classification error and movement initiation effort. The intention classification error measured the controller accuracy in detecting human intentions, both for moving and holding. Movement initiation effort reflected the necessary effort to surpass the threshold from holding to moving. The ideal outcome would be achieving high accuracy in the classification of both holding and moving intentions, while simultaneously minimizing the effort needed for movement initiation.

1) Intention Classification Error: The user intention was quantified in the context of the target matching task, determined based on the real-time elbow angle θ relative to the target position $\bar{\theta}$ (with a ± 5 degree margin). In other words, if the real-time elbow angle fell within the range delineated by the two blue lines:

- $\theta < \bar{\theta} - 5$ $\rightarrow$ user intention: Up
- $\bar{\theta} - 5 \leq \theta \leq \bar{\theta} + 5$ $\rightarrow$ user intention: Hold
- $\theta > \bar{\theta} + 5$ $\rightarrow$ user intention: Down

The controller classification was interpreted based on Δe in relation to the biceps and triceps thresholds β (Fig. 2):

- $\Delta e > \beta_b$ $\rightarrow$ controller classification: Up
- $\beta_t \leq \Delta e \leq \beta_b$ $\rightarrow$ controller classification: Hold
- $\Delta e < \beta_t$ $\rightarrow$ controller classification: Down

At each timestamp, we determined whether there was an error in the controller classification relative to the user intention, along with the magnitude of this error. We termed this error the intention classification error (ϵ). The magnitude of the error was calculated as the deviation from the correct classification

TABLE II
INTENTION CLASSIFICATION ERROR (ϵ)

	Error (ε)	Controller Classification: Up	Hold	Down
User Intention	Up	–	$\lvert\Delta e - \beta_b\rvert$	
	Hold	$\Delta e - \beta_b$	–	$\lvert\Delta e - \beta_t\rvert$
	Down	$\Delta e - \beta_t$		–

(Table II). For instance, if the user intention was to move Up, correct controller classification would require $\Delta e > \beta_b$. Errors occurred when $\Delta e \leq \beta_b$, with an error magnitude of $\epsilon = |\Delta e - \beta_b|$. A 3×3 confusion matrix of classification rate, was calculated. For example, an entry in row 1, column 2 represents the percentage of timestamps that should be classified as Up (user intention) but were incorrectly classified as Hold (controller classification).

To differentiate controller performance during movement and holding phases, we categorized errors based on the user intention to either move or hold. The error rate was then defined as the percentage of misclassified timestamps corresponding to whether the user intention was to move or hold. We normalized the count of errors to determine the error density at each magnitude level. The error density was then fitted to a Gaussian curve to characterize the error (ϵ) distribution for each participant:

$$G(\epsilon) = a \, \exp\left(-\frac{\epsilon^2}{2\sigma^2}\right) \tag{4}$$

a was the peak height of the Gaussian curve, and σ was the standard deviation of the Gaussian curve.

2) Movement Initiation Effort: We measured the EMG magnitude (peak EMG value) for each extension movement in the triceps, and each flexion movement in the biceps across all participants. The EMG magnitudes were normalized for each participant and muscle, using the average peak value of the largest trajectories in the 'Without Obj' sets from the practice trial (i.e. $20^\circ \rightarrow 80^\circ$ for biceps and $80^\circ \rightarrow 20^\circ$ for triceps). These movements were selected as they require the greatest muscle activation, and using peak values during a task is a common method for EMG signal normalization [21].

Four-way mixed ANOVA with three within-subjects factors (User Intention: Move, Hold; Controller: Fixed, Real-time Adaptive; Condition: Without Obj, With Obj) and a between-subjects factor (Order: Fixed Controller first, Real-time Adaptive Controller first) were fit to examine the effects of these factors on the error rate and the error distribution SD (σ). The values were log-transformed when necessary to satisfy the assumptions of normality and homogeneity of ANOVA residuals. Post-hoc pairwise comparisons were performed, and CI_d (95% confidence interval on the difference in means) was calculated. Cohen's d effect size was calculated for each pairwise comparison: small effect ($0.2 < |d| < 0.5$), medium effect ($0.5 < |d| < 0.8$), and large effect ($|d| > 0.8$). Paired t-tests were conducted to compare the error rates, EMG magnitudes and survey responses between the two controllers. The null hypothesis was rejected at a significant level of $p < 0.05$.

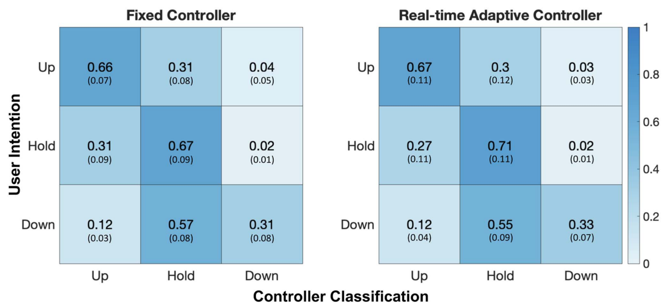


Fig. 4. Confusion matrix for Fixed Controller and Real-time Adaptive Controller. Each entry displays the average classification rate across participants, with the standard deviation indicated in parentheses.

TABLE III
ANOVA RESULTS FOR INTENTION CLASSIFICATION ERRORS

Source	Error Rate F	Error Rate p	Error SD (σ) F	Error SD (σ) p
User Intention	98.0	**<0.001**	418.2	**<0.001**
Controller	1.6	0.207	46.4	**<0.001**
Condition	44.4	**<0.001**	51.8	**<0.001**
Order	2.6	0.140	0.1	0.749
Participant (Order)	1.3	0.117	7.4	**<0.001**
User Intention × Condition	51.0	**<0.001**	3.1	0.082
Condition × Order	8.1	**0.006**	0.2	0.656

* All main effects and only significant interaction effects are displayed.

IV. RESULTS

When the user intention was to hold the position, both Fixed and Real-time Adaptive Controller had significantly higher rates of intention classification errors identified as Up compared to Down (paired t-test: the Fixed Controller: $t_{11} = 11.63, p < 0.001$; the Real-time Adaptive Controller: $t_{11} = 8.14, p < 0.001$) (Fig. 4). Additionally, error rates were higher during downward movements compared to upward movements for both controllers (paired t-test: the Fixed Controller: $t_{11} = 12.55, p < 0.001$; the Real-time Adaptive Controller: $t_{11} = 13.75, p < 0.001$).

Overall, there was no significant difference in the error rate between two controllers (CI$_d$: $[-0.006, 0.055]$, $|d| = 0.236$) (Fig. 5(a)). The presence of additional weight significantly increased the error rates for both controllers when participants were attempting to hold positions ($1.649 < |d| < 2.356$), but no significant changes were observed when trying to move ($0.076 < |d| < 0.436$). Neither Order nor Participant significantly affected the error rate (Table III).

The Real-time Adaptive Controller significantly reduced the error SD compared to the Fixed Controller both with and without the object, during both movement and holding periods ($0.724 < |d| < 1.928$) (Fig. 5(b)). Additional weight led to a significant increase in error SD ($0.937 < |d| < 1.179$). While Order did not significantly impact error SD, participant responses varied during exoskeleton usage (Table III).

The Real-time Adaptive Controller led to a significant reduction in EMG magnitudes during flexion in the biceps without objects, and during extension in the triceps regardless of object presence (all $p < 0.04$) (Fig. 6). No difference was observed between controllers in the biceps EMG magnitudes when holding an object ($p = 0.329$).

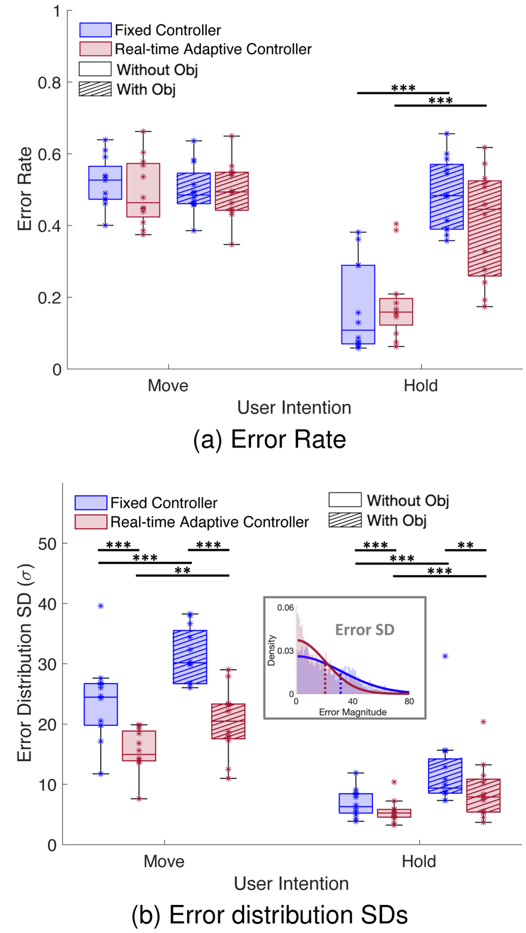


Fig. 5. Intention classification errors. (a) Error rates and (b) Standard deviations (SDs) of error distribution in Fixed Controller and Real-time Adaptive Controller with and without objects. Significant differences are indicated by $*$ (small effect: $*$, medium effect: $**$, large effect: $***$).

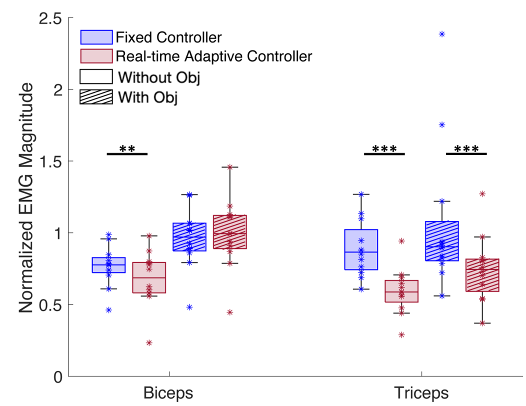


Fig. 6. Comparison of EMG magnitudes at movement initiation between controllers with and without objects. Significant differences are indicated by $*$ (small effect: $*$, medium effect: $**$, large effect: $***$).

No significant differences were observed between the two controllers in survey questions 1–18 ($p > 0.05$) (Table IV). In the overall performance (Q19), each controller was preferred by 5 participants ($|scores| > 5$), while 2 participants viewed them as similar ($|scores| < 5$). Among the 10 participants who expressed a preference, 9 favored the second controller they experienced.

TABLE IV
SURVEY QUESTIONS ON CONTROLLER PERFORMANCE

Questions			Fixed Controller	Real-time Adaptive Controller
01.	**Familiarity**	How familiar are you with the system.	78 ± 18	80 ± 12
02.	**Comfort**	Rate the comfort level of the exoskeleton.	64 ± 24	72 ± 16
03.	**Learning**	Rate your experience learning to use the exoskeleton.	82 ± 12	79 ± 17
04.	**Effort**	How hard did you have to work to accomplish your level of performance.	44 ± 31	37 ± 25
05.	**Fatigue**	Rate the level of fatigue you felt during the task.	41 ± 28	37 ± 20
06.	**Frustration**	How insecure, discouraged, irritated, stressed, and annoyed were you?	15 ± 19	17 ± 24
07.	**Mental Demand**	How mentally demanding was the task?	24 ± 21	25 ± 26
08.	**Physical Demand**	How physically demanding was the task?	33 ± 28	29 ± 21
09.	**Temporal Demand**	How hurried or rushed was the pace of the task?	9 ± 10	12 ± 13
10.	**Task Performance**	How successful were you in accomplishing what you were asked to do?	76 ± 11	77 ± 12
11.	**Effectiveness**	How much did the exoskeleton help you perform the task?	66 ± 21	65 ± 19
12.	**Responsiveness**	How responsive was the exoskeleton?	77 ± 15	80 ± 18
13.	**Muscle Relaxation**	How relaxed were you when holding the position during the task?	65 ± 28	62 ± 26
14.	**Loaded Performance**	How much did the weight affect your performance compared without the weight?	60 ± 18	58 ± 24
15.	**Predictability**	How well are you aware of the system's intent, action, and outputs?	78 ± 16	78 ± 18
16.	**Reliance**	How dependable is the system?	71 ± 18	67 ± 25
17.	**Trust**	How much did you trust the system?	78 ± 17	79 ± 16
18. Imagine using the current controller of the exoskeleton in the following task. How much are you willing to use it versus not?				
(1) Lift a laundry box			60 ± 27	54 ± 35
(2) Pick up a water bottle to drink			38 ± 37	38 ± 35
(3) Pull (e.g. Pulling a door handle or drawer)			48 ± 33	47 ± 31
(4) Hang an object (e.g. hanging a coat hanger, fabric item, etc.)			34 ± 38	39 ± 32
(5) Stabilize an object (e.g. when you are moving a heavy delivery box from outside to home)			77 ± 17	65 ± 30
19.	**Comparison**	How do you feel about the two controllers?	36 ± 29	61 ± 19

* Questions 1-18, rated on a 0-100 scale, were completed after the 2nd and 4th modules.
* Question 19, rated from -100 to 100, was only completed after the 4th module.
* Higher scores on Q1-3,10-13,15-18, lower on Q4-9,14 reflect more positive participant perceptions.

V. DISCUSSION

This study evaluated two controllers for EMG-based powered upper limb exoskeletons in an elbow target tracking task, incorporating both transitory and hold periods. A nominal Fixed Controller used the differences in biceps and triceps contractions to infer user intentions for elbow movement and required users to adopt an *Exoskeleton MP* to operate the system efficiently. The Real-time Adaptive Controller added elbow angle data to capture the user's current motor strategy (the *Learned MP*), facilitating effective exoskeleton usage without the need for users to master the *Exoskeleton MP*.

Our hypothesis regarding the accuracy of intention classification was not supported. No significant difference was observed in error rate between the two controllers. However, the error distribution SDs were significantly lower in the Real-time Adaptive Controller across all scenarios, whether with or without objects, and during both movement and holding periods. Considering the nature of proportional myoelectric control, minimizing error magnitudes is crucial, as larger errors lead to increased resistance. These minor errors might also provide users with feedback, prompting them to modulate their muscle contractions to the desired level [22]. It is important to note that measuring true user intention was infeasible. Using the elbow angle relative to the target angle as a surrogate measure for user intention likely contributed to higher error rate. Discrepancies arose from factors such as early movement initiation in anticipation of the next target, delayed responses due to shifts in attention, or overcorrection in positioning to the exact target center when within the acceptable region. These errors, more indicative of human performance variability than controller performance, impacted the accuracy metrics used in our study.

The hypothesis related to movement initiation effort was supported. The Real-time Adaptive Controller displayed a reduction in EMG magnitudes during the initiation of both flexion and extension movements. In traditional proportional myoelectric control, facilitating movement initiation often leads to challenges in maintaining positions, as slight muscle activation could exceed the lower threshold. The Real-time Adaptive Controller maintained the error rate and even reduced error magnitudes, effectively addressing this dilemma.

Higher error rates in extension movements compared to flexion could be attributed to the greater Δe change required to surpass the threshold (from $f_{learned}$ to the lower and upper boundary, as shown in Fig. 2(c)), especially at flexed elbow angles. In the current setup, where users relax their muscles to maintain position, actively contracting the triceps is necessary for extension movements. However, one participant noted that they normally extended their elbow by simply relaxing their arm and allowing gravity to assist, which brings into question our initial assumption that position maintenance equates to no muscle contraction. In some situations, encouraging users to apply slight contractions to hold positions, while relaxing to extend, could provide enhanced robustness against potential perturbations during the holding period [23].

Question 19 indicated that most participants (9 out of 12) preferred the second controller they used, suggesting improved interaction with the exoskeleton over time regardless of the controller type. However, the preference was stronger for the Real-time Adaptive Controller when it was used second (61 vs. 36), indicating a potential higher favorability among participants for it. However, participants did not report significant differences in specific aspects. Enhancing the controller's legibility by providing users with feedback about its current status and upcoming movements could potentially improve their perceptions [15]. Previous research has also underscored that users need to experience changes exceeding a certain threshold to perceive differences or improvements in an exoskeleton [24], [25]. While participants may not have directly perceived the effort benefits, they might have implicitly experienced its advantages, which has been examined using other metrics, like economic value [26].

The hardware constraints that cap thresholds at 65% might have limited the Real-time Adaptive Controller's performance, especially when larger thresholds were often desired at flexed elbow angles. We compared the performance of the Real-time Adaptive Controller to that of the Fixed Controller, both initialized with identical parameter settings for all participants, eliminating the need for a participant-specific calibration phase. However, the performance of the Fixed Controller could vary if participants were allowed to select their own parameter settings. The *Learned MP* currently updates using a 0.8-second window for data extraction. A larger window might restrict valid data for updates due to stricter criteria, while a smaller window could include data that does not accurately reflect user intention. Future research should identify the optimal window size or explore alternative fitting methods. Future studies could also consider integrating embedded pressure sensors for automatic object grasp detection to switch between conditions. Although the Real-time Adaptive Controller functioned for individuals who have not fully acquired the *Exoskeleton MP*, it did not guide users toward attaining the *Exoskeleton MP*. Therefore, ongoing efforts to encourage continuous adaptation are essential to maximize the benefits of the exoskeleton. This study introduced an adaptive exoskeleton controller designed to handle complex movements containing both dynamic and static tasks, expanding upon previous adaptive algorithms that were primarily effective in cyclic movements. We started with two muscles that control the elbow joint and lays the groundwork for future expansions to multi-degree-of-freedom systems using a similar approach of capturing the user's motor program.

VI. Conclusion

In this study, we introduced a Real-time Adaptive Controller, designed to track the user's current motor program and use it for intention classification. This controller mitigated the common trade-off in conventional proportional myoelectric controllers between movement facilitation and holding stability. It reduced error magnitudes for both movement and holding periods, while decreasing movement initiation efforts at the same time. However, further enhancements are necessary to improve participant perceptions. Future work will extend the algorithm for more accurate and timely tracking of motor programs, and guiding users in learning the ideal motor program.

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