

Impact of Shoulder Exoskeleton Assistance on Human Upper-Limb Motor Primitives

Niromand Jasimi Zindashti, Negar Riahi, Ali Golabchi, Mahdi Tavakoli, and Hossein Rouhani¹

Abstract—Human upper-limb movements are known to exhibit robust kinematic features, including bell-shaped velocity profiles and the two-thirds power law. These features are interpreted as signatures of motor primitives underlying human movement planning. While wearable exoskeletons are increasingly used to reduce physical load, their influence on these motor primitives remains unexplored. This study investigates whether upper-limb kinematic motor primitives are maintained during movements performed with a shoulder-support exoskeleton. Five healthy participants performed vertical and complex three-dimensional upper-limb movements under three conditions: no exoskeleton, low-support exoskeleton, and high-support exoskeleton. Movement elements were extracted based on velocity zero-crossings of hand kinematics. The experimental velocity profiles of these elements were compared to a bell-shaped profile, and the scaling relationship between mean velocity and movement displacement was evaluated. Results showed strong agreement with bell-shaped velocity profiles, with high correlations to the theoretical profile (0.86-0.87), and scaling exponents close to the theoretical two-thirds value (confidence intervals range of [0.57, 0.73]). Statistical analysis revealed no significant effects of exoskeleton assistance level or movement type. These preliminary findings suggest that shoulder-support exoskeleton assistance does not disrupt the fundamental kinematic structure of upper-limb motor primitives, maintaining predictable kinematic motor primitives despite load redistribution. This supports the use of model-based assistance, intent inference, and primitive-based control strategies in wearable robotics, assuming that fundamental movement structure remains intact under exoskeleton support.

I. INTRODUCTION

Human upper-limb movements exhibit consistent kinematic patterns despite the mechanical redundancy and high dimensionality of the musculoskeletal system. Extensive research in motor control has shown that complex voluntary movements can be decomposed into a finite set of elementary components, commonly referred to as motor primitives [1]. These primitives reflect fundamental strategies of the neuromotor system, allowing the central nervous system (CNS) to generate a wide range of movements in an optimum way.

An important feature of motor primitives is the presence of bell-shaped velocity profiles during goal-directed movements. Such profiles have been consistently observed in upper-limb reaching, drawing, and manipulation tasks and are often interpreted as the outcome of optimal control strategies such

as minimum jerk or minimum torque change [2]. Beyond profile shape, movement primitives exhibit robust scaling laws that link kinematics to spatial characteristics. In particular, the mean absolute velocity of a movement scales with its displacement according to a two-thirds power law [2], [3], a relationship that holds across different movement amplitudes and directions [4], [5]. The persistence of this law suggests that it reflects intrinsic features of motor planning rather than task-specific factors [6].

Importantly, even three-dimensional (3D) complex movements can be decomposed into sequences of such primitives [2]. Each element has bell-shaped velocity profiles and consistent scaling behavior, supporting the idea that the CNS constructs complex movements by combining these simpler elements rather than continuously replanning full trajectories [7], [8]. These principles have become foundational not only in neuroscience but also in robotics and human-machine interactions, where motor primitives are increasingly used for movement prediction, intention estimation, and adaptive control [9], [10].

Furthermore, wearable robotic exoskeletons have gained attention as assistive technologies for reducing physical load, mitigating fatigue, and enhancing performance during demanding tasks [11], [12], [13]. Upper-limb exoskeletons, particularly shoulder-support exoskeletons, are widely investigated for industrial and occupational applications involving sustained overhead or repetitive movements [14], [15]. While exoskeletons provide biomechanical benefits, their influence on the neural organization of movement has not been explored. In practice, user acceptance and effectiveness often vary across tasks and assistance levels, suggesting that robotic support may interact with human motor control in different ways as the assistance level changes [16].

A critical question is whether robotic assistance preserves the fundamental kinematic structure of human movement. If exoskeleton support alters the shape of velocity profiles or changes scaling relationships between velocity and displacement, this would imply an interaction at the level of motor planning rather than only load compensation. Such effects may depend strongly on the level of assistance provided, as low-support conditions may act as subtle perturbations, whereas high-support conditions could dominate the dynamics of movement and reduce the user's contribution. Understanding how different assistance levels influence motor primitives is therefore essential.

¹This project was funded by the Natural Sciences and Engineering Research Council of Canada in partnership with Alberta Innovates (Grant # ALLRP 567348 – 21).

N. J. Z. (jasimizi@ualberta.ca), N. R. (riahi@ualberta.ca), A. G. (alirezal@ualberta.ca), and H. R. (hrouhani@ualberta.ca), corresponding

author) are with Department of Mechanical Engineering, University of Alberta, Edmonton, AB, Canada.

M. T. (mtavakol@ualberta.ca) is with Department of Electrical and Computer Engineering, University of Alberta, Edmonton, AB, Canada

In addition to assistance magnitude, the type of movement may play a critical role. Linear movements impose relatively simple kinematic and coordination demands and are often used to study motor laws. In contrast, complex 3D movements require continuous coordination across multiple joints and spatial dimensions, potentially engaging different planning strategies or neural resources.

Despite the relevance of these factors, most prior studies on upper-limb exoskeletons have focused on performance metrics such as muscle activation, joint loading, and endurance [14], [17]. While informative, these performance metrics do not directly assess whether the CNS preserves its intrinsic movement organization under exoskeleton assistance. A smaller number of studies have examined kinematic smoothness or variability [18], but testing whether core motor invariants, such as bell-shaped velocity profiles and the two-thirds power law, are maintained across different assistance levels and movement complexities remains unexplored.

Addressing this lack of investigation into these motor invariants has important implications in two ways. First it sheds light on the robustness of motor primitives under external mechanical assistance and clarifies whether these primitives represent fixed neural constraints or adaptive patterns sensitive to assistance. Second, from a wearable robotics perspective, it informs the validity of primitive-based movement prediction and control strategies for exoskeletons [19]. If primitives are preserved across support levels and task types, controllers can exploit these invariants to provide intuitive and predictive assistance. If not, control algorithms must explicitly account for assistance-based changes in motor movement predictions. An example of similar approaches is the use of dynamic primitive movements, where an adaptive dynamic movement primitive-based controller enables a wearable exoskeleton to accurately predict and assist a wide range of discrete lifting movements while preserving natural joint kinematics [19], [20], [21].

The present study investigates whether the upper-limb kinematic motor primitives are preserved during movements performed with a shoulder-support exoskeleton under varying conditions. Participants performed linear and complex 3D movements under three assistance levels: no exoskeleton, low support, and high support. Hand velocities were analyzed to identify movement elements using velocity zero-crossings. We examined whether the extracted elements retained bell-shaped velocity profiles and whether the scaling exponent relating mean absolute velocity to movement displacement deviated from the theoretical two-thirds value as a function of assistance level and movement type.

II. METHODS AND MATERIALS

A. Theoretical Background

A key finding from studies of curved hand trajectories is that movement speed is not arbitrary but is linked to the geometry of the movement. Specifically, the one-third power law states that the instantaneous velocity $v(t)$ increases with the radius of curvature $R(t)$ [5]:

$$v(t) \cong kR(t)^{\frac{1}{3}} \quad (1)$$

where k is a constant depending on movement characteristics. This relationship is consistent with the widely accepted minimum-jerk principle, which proposes that human movements tend to minimize abrupt changes in acceleration [22]. To incorporate the influence of movement duration, Hoff introduced a model that defines the cost function for a two-dimensional movement [23]:

$$J = K \int_0^T (\ddot{x}(t)^2 + \ddot{y}(t)^2) dt + T \quad (2)$$

where T is movement time, $\ddot{x}(t)$ and $\ddot{y}(t)$ represent jerk components, and K is a weighting factor. Assuming static boundary conditions, Hoff derived the relationship between the duration of the movement (T) and the associated displacement (D):

$$T = (60D)^{\frac{1}{3}} K^{\frac{1}{6}} \quad (3)$$

Additionally, minimizing the above cost function (J) for point-to-point movements yields smooth, bell-shaped velocity profiles (Eq. 4). Combining Eqs. (3) and (4) will result in a scaling between movement size and timing. Importantly, these movements follow a two-thirds power law, where mean velocity v scales with displacement D (Eq. 5). While originally developed for two-dimensional movements, recent studies strongly support these fundamental equations for complex 3D movements [2].

$$v(t) = \frac{D}{T} (30\tau^2 - 60\tau^3 + 30\tau^4), \quad \tau = \frac{t}{T} \quad (4)$$

$$\bar{v} \propto D^{\frac{2}{3}} \quad (5)$$

B. Participants

Five healthy individuals (two females and three males, age: 30 ± 3 years, weight: 61 ± 8 kg, and height: 170 ± 6 cm) without any neurological conditions affecting motion control were recruited to participate in the experiments. The study was approved by the research ethics board of the University of Alberta, ID: Pro00109264.



Figure 1: ShoulderX exoskeleton and its features

C. Exoskeleton

Passive exoskeletons lie at the minimal-intervention end of wearable robotics, assisting solely through mechanical elements, without sensing or active control. As such, their behavior provides a critical and exploratory baseline for

examining how human motor control responds to external mechanical assistance before the introduction of powered actuation or adaptive control strategies. The shoulder-support exoskeleton, ShoulderX (SuitX, Emeryville, United States), is a passive wearable robotic system used to provide assistive torque during the movements (Figure 1). The exoskeleton uses a spring to provide support, which applies force to the upper arms and creates a moment at the shoulder joint for arm elevation movements. The support level can be changed continuously from a low level (level 1) to a high level (level 5). this exoskeleton can provide 5-20 Nm torque for the shoulder joints, with torque profiles reported in [24]. The exoskeleton was set to provide maximum torque at 90° of arm elevation. The exoskeleton's weight is 3.17 kg, and its setting can be adjusted to fit the back frame and under-arm support point. The exoskeleton was fitted and adjusted individually to ensure proper fitting.

D. Experimental Procedure

Participants performed two upper-limb movements (Figure 2). The first movement (vertical movement) consisted primarily of vertical arm movements, with repeated upward and downward motions along the vertical axis in the sagittal plane. The second movement (complex movement) involved complex 3D movements. To make the task consistent, the participants were asked to trace an imaginary figure-eight (8) pattern, mainly in the coronal plane. The vertical movement was performed three times: right hand, left hand, and both hands.

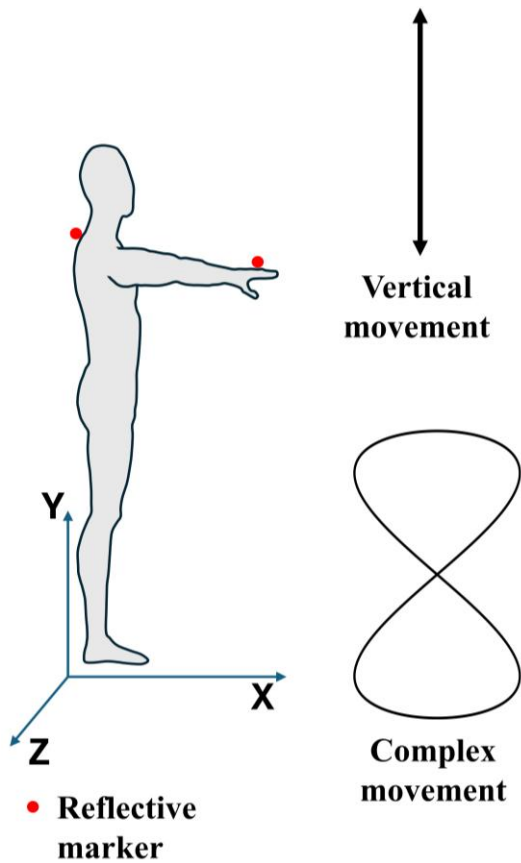


Figure 2: Data collection with two movement.

As it was found to be difficult to coordinate both hands for the complex movement, this movement was performed twice, with each hand independently.

All tasks were performed while participants stood upright in a comfortable, self-selected stance. Participants were instructed to maintain a stable posture and avoid unnecessary trunk motion during task execution. Tasks were performed under three exoskeleton conditions: (1) without the exoskeleton, (2) with the exoskeleton providing low assistance (level 2 of exoskeleton setting), and (3) with the exoskeleton providing high assistance (level 5 of exoskeleton setting). The order of conditions was randomized across trials to prevent systematic ordering effects. For all tasks, participants were instructed to move naturally at a comfortable, self-selected pace. Before the experiment, participants were asked to practice with different modes of exoskeletons to familiarize themselves.

Upper-limb kinematics were recorded using a camera-based motion capture system (Vicon, Oxford, UK) operating at a sampling frequency of 100 Hz. The motion capture coordinate system was aligned with the anatomical reference frame, with axes corresponding to the antero-posterior (X), vertical (Y), and medio-lateral (Z) directions. Reflective markers were placed on the spinous process of the seventh cervical vertebra (C7) and on the back of both hands (3rd Metacarpophalangeal joint). Marker placement was kept consistent across all experimental conditions.

Data Processing

The position signals were low-pass filtered using a fourth-order filter with a cutoff frequency of 10 Hz. Velocities of the hand markers were computed relative to the C7 marker by numerical differentiation of the filtered position data. Movement elements were identified independently along each axis by detecting zero-crossings in the corresponding velocity time series, which defined the temporal boundaries of individual movement components. Only movement elements that exceeded the minimum threshold for displacement (10 mm) and duration (100 ms) were retained to ensure reliable

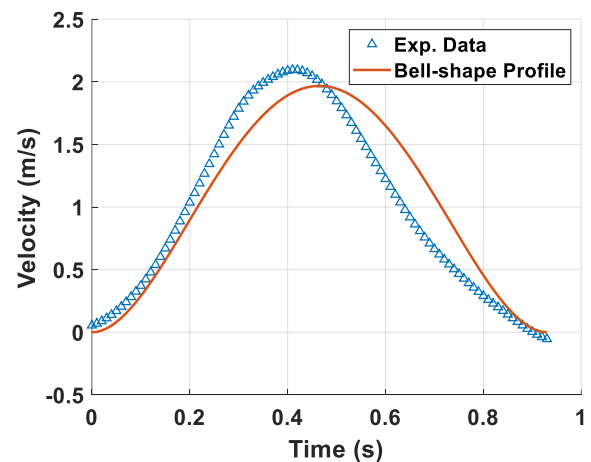


Figure 3: An example of the comparison between experimental velocity profiles of movement elements and the theoretical bell-shaped velocity profile for the calculation of Pearson's correlations.

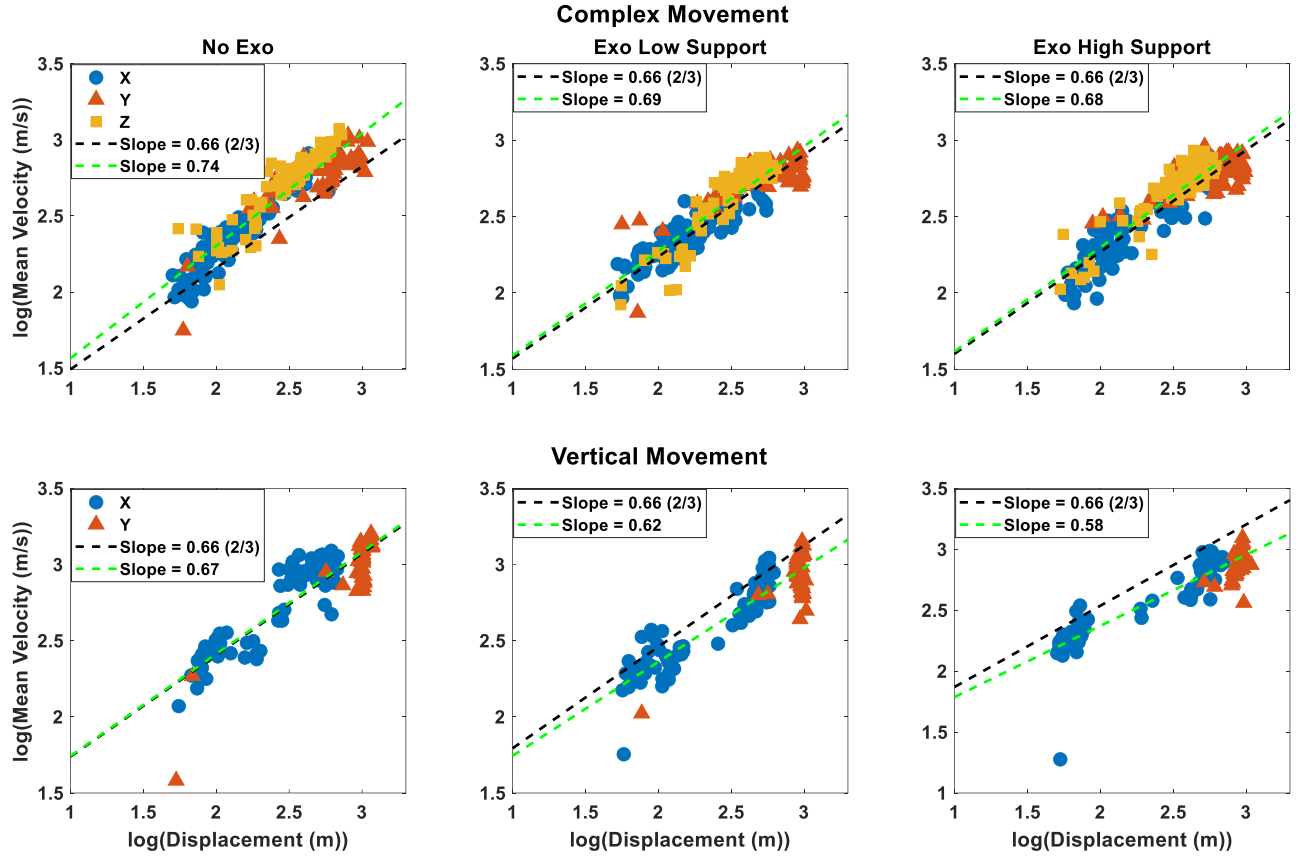


Figure 4: Relationship between experimental values of displacement (D) and mean velocity (v) against a $2/3$ line in log-log scale (Eq. 5). Columns show data for different exoskeleton conditions (no exo, exo with low support, and exo with high support), and two rows show data for two movement types (complex movement and vertical movement). Data points are shown in different colors and shapes for three directions, and the regressed line (green dashed), along with the theoretical $2/3$ power-law exponent (black dashed), is also plotted for visual comparison. It should be noted that in vertical movement, the displacement in the Z axis (medio-lateral direction) was minimal, and therefore its data was excluded.

detection given the signal-to-noise characteristics of the recordings [2]. Movement elements were identified independently along each axis by detecting zero-crossings in the corresponding velocity time series, which defined the temporal boundaries of individual movement components. Only movement elements that exceeded the minimum threshold for displacement (10 mm) and duration (100 ms) were retained to ensure reliable detection given the signal-to-noise characteristics of the recordings [2]. The temporal profiles of the extracted movement elements were compared to a theoretical bell-shaped velocity profile (Eq. 4) using Pearson correlation coefficients (Figure 3). In addition, the relationship between mean absolute velocity and movement displacement was examined to assess adherence to the two-thirds power law (Eq. 5). This relationship was evaluated using log-log linear regression, and the resulting scaling exponent (β : $\bar{v} \propto D^\beta$) was compared against the theoretical value of $2/3$.

Data were analyzed using a linear mixed-effects model to compare the three exoskeleton conditions (no exoskeleton, low-support exoskeleton, and high-support exoskeleton) and two movement conditions (vertical and complex movement). Condition was included as a fixed effect, and participant was included as a random effect to account for repeated measurements within participants. This approach was chosen

as we had unequal numbers of repetitions across conditions and participants. Model significance was assessed using marginal F-tests, and post-hoc comparisons between conditions were conducted using linear contrasts of the fixed effects. Furthermore, as the sample size was small, bootstrap 95% confidence intervals were calculated for exponent values (β), with 10,000 resamples, to characterize the variability. This non-parametric approach provides robust uncertainty bounds.

III. RESULTS

As shown in Figure 4, experimental data from different exoskeleton conditions, movement types, and movement directions largely follow a two-thirds power law. Specifically, the results of linear regression show average exponent (β) values of 0.74, 0.69, and 0.68 for no exo, exo with low support, and exo with high support conditions, respectively, for complex movement. Additionally, average exponent values for vertical movements are 0.67, 0.62, and 0.58 for No Exo, exo with low support, and exo with high support conditions, respectively. Considering all exoskeleton and movement conditions, the 95% bootstrap confidence intervals showed the range of [0.57, 0.73].

The mean $\pm$ SD of the Pearson correlation coefficients between velocity profiles of experimental movement elements and theoretical bell-shaped profiles were found to be 0.88 ± 0.13 , 0.87 ± 0.12 , and 0.86 ± 0.14 for no exo, exo with low support, and exo with high support conditions, respectively (Figure 5). Furthermore, for both movement types (vertical and complex movement), the mean $\pm$ SD of these correlation coefficients was 0.87 ± 0.13 . Results of the linear mixed-effects model indicated no significant main effect of exoskeleton condition on the correlation coefficients ($p = 0.25$), and no significant main effect of movement type ($p = 0.97$). Post-hoc comparisons confirmed that no significant differences were observed between any condition pairs.

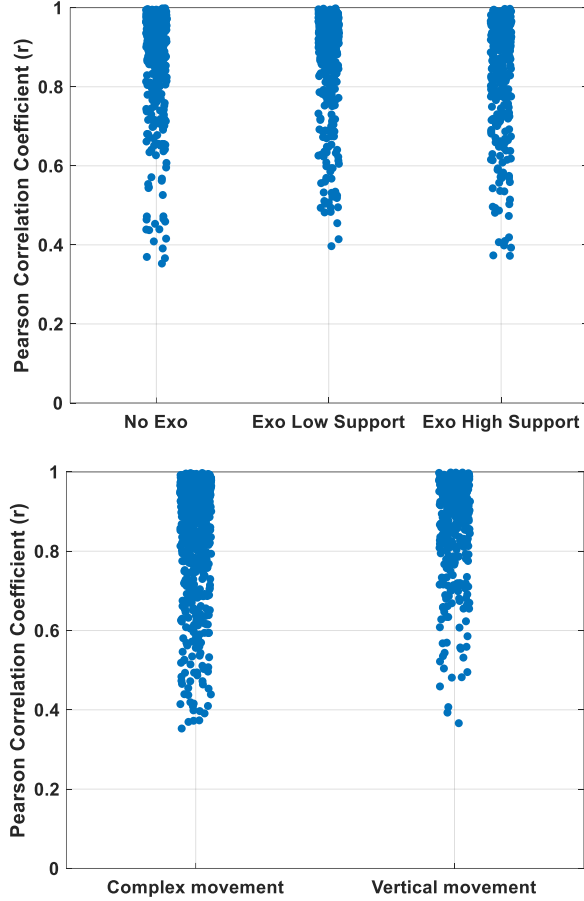


Figure 5: Pearson correlation coefficients grouped by exoskeleton and movement conditions.

IV. DISCUSSION

Our preliminary findings demonstrate that key motor invariants, including bell-shaped velocity profiles and the two-thirds power law, remain largely unchanged across no-support, low-support, and high-support exoskeleton conditions. These preliminary results suggest that shoulder-support exoskeleton assistance does not substantially alter the intrinsic kinematic organization of upper-limb movements at the level of motor primitives, although the small sample size limits the statistical power and the generalizability of the findings. Furthermore, although the exoskeleton reduces the muscular effort, a user remains responsible for planning and executing the movement, allowing the central nervous system to generate trajectories according to its preferred motor strategies. It is also possible

that assistance beyond a certain threshold, such as that provided by an active exoskeletons, may influence movement planning and lead to changes in these motor invariants.

The absence of significant differences between vertical and complex movements indicates that motor primitives may remain consistent across different movement types. In line with previous studies [2], this finding supports the notion that complex movements can be decomposed into sequences of elements with consistent kinematic properties, and that this structure is preserved during assisted movement.

Previous studies have used muscle synergies, as motor primitives, for controlling wearable robots [25], [26]. In this study, we show that kinematic-based motor primitives are preserved when an exoskeleton provides assistance. Therefore, these primitives can be used, in combination or separately, for the movement prediction and control of exoskeletons.

The preservation of kinematic motor primitives under passive exoskeleton assistance has important implications for wearable robotic control design. Our findings suggest that, even in the presence of external mechanical support, human movement remains organized and predictable. This implies that exoskeletons can rely on human-led motion generation without needing to compensate for altered planning strategies. As a result, shared-control and intent-prediction approaches can be simplified, using velocity profiles and scaling laws to predict motion and modulate assistance with minimal sensing and computational overhead. More broadly, these results motivate the extension of primitive-based control frameworks to powered exoskeletons, where the robot contributes actively to motion generation. Establishing whether such robustness persists under active assistance represents a key next step toward co-adaptive human-robot control policies that remain intuitive, stable, and biologically grounded.

By analyzing the extracted elements, we found that some low correlations observed in Figure 5 may be due to noise in the motion data, which can affect how well movement elements are automatically identified. The results of element decomposition depend on the values chosen for parameters such as the minimum displacement and movement duration, which were selected based on the methodology reported by Miranda et al. [2]. If not optimum, these thresholds can lead to wrong or noisy elements. Therefore, in the future, we will conduct further sensitivity analysis to determine appropriate threshold values and to improve the reliability of the movement decomposition and correlation results.

Additionally, the experimentally estimated exponent shown in Figure 4 exhibits slight deviations from the theoretical $2/3$ value for two exoskeleton conditions in vertical movement. Closer inspection of the data points suggests that these deviations are not entirely attributable to exoskeleton assistance. Instead, they are strongly influenced by the unequal distribution of data points, particularly the high density of points corresponding to large displacements and higher mean velocities. Although these points individually lie close to the $2/3$ power law, they are clustered within a narrow region where their local orientation is not well aligned with the theoretical $2/3$ slope. As a result, the high concentration of points in this region disproportionately influences the regression, changing

the direction of the fitted line. This observation highlights an important limitation of direct regression approaches, which may not reliably reflect alignment with the theoretical 2/3 power law under such data distributions.

This study has some limitations that should be acknowledged. First, as a proof-of-concept study, we acknowledge that the small sample size reduces the statistical power to detect subtle effects of exoskeleton assistance or interactions with movement type and the results are primarily applicable to a similar population. Future studies with larger and more diverse participant groups will be conducted to confirm the generalizability of these results. Second, the effects of the exoskeleton were assessed during short-term usage. Participants interacted with the exoskeleton during a single experimental session; therefore, the results primarily reflect immediate responses to assistance. Long-term use may lead to motor adaptation, changes in movement strategies, or altered reliance on external support, potentially affecting the organization of motor primitives. Future work should therefore investigate whether the preservation of motor invariants persists after extended training or prolonged occupational use of exoskeletons.

V. CONCLUSION

This study provides preliminary evidence that fundamental upper-limb motor primitives are preserved during movements performed with a shoulder-support exoskeleton, across different assistance levels and movements. The maintenance of bell-shaped velocity profiles and the two-thirds power law suggests that passive exoskeleton assistance may not disrupt the intrinsic organization of human movement at the level of motor planning. From a wearable robotics perspective, these findings indicate that human motion may remain structured and predictable under support, supporting the use of primitive-based frameworks for exoskeleton control and assistance modulation. Future studies will be conducted with a larger and more diverse sample size as well as active exoskeletons to confirm the generalizability of the findings.

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