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Quantification and visualization of coordination during non-cyclic upper extremity motion

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ABSTRACT

There are many design challenges in creating at-home tele-monitoring systems that enable quantification and visualization of complex biomechanical behavior. One such challenge is robustly quantifying joint coordination in a way that is intuitive and supports clinical decision-making. This work defines a new measure of coordination called the relative coordination metric (RCM) and its accompanying normalization schemes. RCM enables quantification of coordination during non-constrained discrete motions. Here RCM is applied to a grasping task. Fifteen healthy participants performed a reach, grasp, transport, and release task with a cup and a pen. The measured joint angles were then time-normalized and the RCM time-series were calculated between the shoulder-elbow, shoulder-wrist, and elbow-wrist. RCM was normalized using four differing criteria: the selected joint degree of freedom, angular velocity, angular magnitude, and range of motion. Percent time spent in specified RCM ranges was used as a composite metric and was evaluated for each trial. RCM was found to vary based on: (1) chosen normalization scheme, (2) the stage within the task, (3) the object grasped, and (4) the trajectory of the motion. The RCM addresses some of the limitations of current measures of coordination because it is applicable to discrete motions, does not rely on cyclic repetition, and uses velocity-based measures. Future work will explore clinically relevant differences in the RCM as it is expanded to evaluate different tasks and patient populations.

1. Introduction

Telemedicine provides opportunity to bring expertise of skilled clinicians to non-hospital environments. It has been demonstrated to improve patient outcomes at costs lower than clinical visits (Heidenreich et al., 2011; Noel et al. 2004; Turvey et al., 2007; Hunkeler et al., 2000; Landow et al., 2014). Rehabilitation using telemedicine is less studied, but the technology is promising (Russell, 2007; Kairy et al., 2009; Gregory et al., 2011). The care provided by tele-rehabilitation includes diagnostic patient assessment, therapeutic intervention, and patient performance monitoring. Tele-rehabilitation also aims to disambiguate differences in patient performance between clinical visits that arise from patients (1) correctly performing, (2) incorrectly performing, or (3) not performing prescribed home exercises; this information could inform patient treatment (Stirling and McLean, 2016).

One challenge in creating tele-monitoring systems is robustly quantifying features monitored by clinicians (e.g. coordination, fluidity, etc.) in ways that support decision-making (Stirling and McLean, 2016). Many current tele-monitoring systems focus on outcome-based metrics for task completion (i.e. completion time). However, there is a need for performance-based metrics that enable deeper insight by disambiguating desired and undesired motor patterns used to complete the task (Malley et al., 2014). These desired motor patterns may change due to the heterogeneity of treatment protocols and pathologies between patients. Any new performance-based metrics must be developed with appropriate normalization schemes, allowing for the metric interpretation in the context of the executed task and independent of differing joint characteristics. Finally, new metrics must be presented intuitively in a way that decreases the workload necessary for decision-making (Schroeder et al., 2014; Wickens, 2002; Rouse and Morris, 1986).

In this work, we present methodology for quantifying and normalizing coordination. Human movement involves manipulating many degrees of freedom (DoF) to perform an action. Bernstein

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(1967) defines coordination as the organizational mastery of these DoF, with complexity arising from the multiple kinematic solutions available in human dynamics. Turvey (1990) decomposes coordination into two categories—(1) kinematic patterns and (2) neural control—and explains that task and environment lead to differences in DoF regulation despite the same end goal. This definition aligns with the clinical interpretation provided by Stirling and McLean (2016), which describes coordinated movements as motions with appropriate, non-pathologic motor patterns across multiple limbs. Current measures that represent the kinematics of coordination are (1) continuous relative phase (CRP) and (2) vector coding. Both methodologies involve quantifying coordination using phase-space trajectories, where vector coding relies on position signals (Scholz and Kelso, 1989) and CRP uses position and velocity signals (Sparrow et al., 1987). These measures have mostly been applied to cyclic motion (e.g., gait (Chiu et al., 2015; Heiderscheit et al., 2002) and swimming (Schnitzler et al., 2008)) as they produce phase portraits. While there is justification for analyzing discrete tasks using CRP (e.g. basketball shooting (Robins et al., 2006)) as it can assess coordination variability between trials, discrete motions preclude the estimation of time continuous measures (e.g., relaxation time, settling time) (Lamb and Stöckl, 2014). Previous work highlighted the non-intuitive results generated by vector coding and CRP, making it difficult to infer the original motor patterns (Miller et al., 2010; Lamb and Stöckl, 2014; Peters et al. 2003). Peters et al. (2003) highlights that CRP should be used to understand relationships in phase-space and should not be used to make interpretations regarding the original time-series. This drawback was also mentioned by Lamb and Stöckl (2014) in a review of CRP highlighting space for a new form of dynamic coordination analysis that is more descriptive and easier to interpret.

Considering these limitations and the above definitions, we present a new, velocity-based coordination metric and accompanying normalization scheme for non-constrained, non-cyclic motion to quantify coordination between body segments, called the Relative Coordination Metric (RCM). This metric estimates coordination of kinematic movements by defining coordination as a degree of relative motion between two body segments. This definition incorporates the kinematic nature described by Bernstein (1967) and Turvey (1990), and also allows motor patterns to be visualized based on the degree of relative motion. In this initial work, upper extremity coordination patterns during a grasp/release task in a healthy population were used to assess the effect of various normalization schemes, as well as specific variations of the task on RCM interpretation. Previous work (Beckers et al., 2015; Olivier et al., 2007; Soechting and Lacquaniti, 1981; Lacquaniti and Soechting, 1982) demonstrated varying kinematic relationships between the shoulder, elbow, and wrist joints during reach/grasp tasks due to different motion trajectories and objects grasped. Thus, to examine task and environmental concerns expressed by Turvey (1990), two objects and two reach/grasp trajectories were evaluated to assess if RCM was sensitive to these variations. As RCM is a velocity-based metric, it is important to consider how underlying differences in joint range of motion (RoM) and DoFs affect the estimation. Thus, we consider normalizing RCM using joint-specific parameters to compare between body segments. As RCM is expected to naturally vary during different stages within grasp/release, we considered how RCM changes during five predefined stages (50% reach, grasp, 50% transport, release, and 50% return). In addition to considering the RCM time-profile, we also defined a time-independent task composite measure of the percent time in a coordination zone ($\hat{t}_{\pm Z_n}$), where we discretized the range of possible RCM values. We evaluated the hypotheses that there was a difference in RCM within the grasping task when (1) different normalization schemes were implemented and (2) during the five task stages; and that there was a difference in $\hat{t}_{\pm Z_n}$ (3) when grasping a cup vs. a pen, and (4) when the task involved different motion trajectories (moving towards or away from the torso).

2. Methods

2.1. Definition of relative coordination metric (RCM)

We define coordination as the degree of relative motion between two body segments, specifically the relative velocity. From this, we define the relative coordination metric (RCM), where ρ_{12} is the RCM between body segment 1 and 2. The aim of the RCM is to quantify the level of coordination between two body segments using velocity-based measures that inform on the underlying kinematics. ρ_{12} is defined with units of degrees over the range $-90^\circ \leqslant \rho_{12} \leqslant 90^\circ$, such that $\rho_{12} = 0^\circ$ represents a movement in which both segments are moving synchronously. $\rho_{12} = +90^\circ$ represents motion in which only segment 1 is moving, while $\rho_{12} = -90^\circ$ represents motion of only segment 2. Values in between represent motions with varying degrees of segment domination. When neither segment is moving, ρ_{12} is undefined and represents no motion. While this metric quantifies relative coordination, a value of 90° or 0° does not imply bad or good coordination. To determine overall task coordination, both the RCM and an understanding of the underlying task must be considered simultaneously.

To start, we consider the angular velocity of each body segment about its proximal joint. Human kinematic models assume different numbers of rotation axes depending on the joint, and the angular velocities of the body segments measured are projections onto these axes. The total angular velocity for each segment is calculated by taking the L^2-norm of the measured components about these axes. To appropriately compare joints with varying characteristics and DoF, we modify the L^2-norm angular velocity of body segment i at time t as follows:

$$\Omega_i(t) = \frac{\sqrt{\sum_{n=1}^{N}\left(\frac{\omega_n(t)}{j_n}\right)^2}}{N * J_T} \tag{1}$$

where N is the number of joint DoF, $\omega_n(t)$ is the angular velocity component of segment i about joint axis n at time t, j_n is an axis-specific normalization parameter, and J_T is a normalization parameter encompassing all joint axes.

Using Eq. (1), the RCM is defined as:

$$\rho_{12}(t) = 2\tan^{-1}\left(\frac{\Omega_1(t)}{\Omega_2(t)}\right) - 90^\circ \tag{2}$$

where $\rho_{12}(t)$ represents the RCM between body segments 1 and 2 at time t, and $\Omega_1(t)$ and $\Omega_2(t)$ are the normalized L^2 angular velocity norms of body segments 1 and 2, respectively. To achieve a range between 90° and −90°, the inverse tangent is scaled and a phase shift applied. This definition of ρ_{12} therefore achieves the previously stated goals for this metric: ρ_{12} approaches 0° when $\Omega_1 \approx \Omega_2$, approaches +90° for $\Omega_1 \gg \Omega_2$, and approaches −90° for $\Omega_1 \ll \Omega_2$. At small Ω_n, ρ_{12} can amplify measurement noise, which results in inaccurately favoring one segment over another. Therefore, it is necessary to set a minimum velocity threshold to avoid this effect. For this study, a minimum velocity of the wrist was used as an indication that motion had begun (see Section 2.3). This work considers five normalization schemes (Table 1) accounting for the DoFs, maximum angular velocities, RoM, and maximum angular magnitudes, while comparing to a baseline of no normalization.

As the RCM is a time-series metric, we defined percent time in a coordination zone ($\hat{t}_{\pm Zn}$) to provide a composite overview on the

Table 1
Definitions of normalization parameters.

	Normalization scheme	N	j_n	J_T
A.	None	1	1	1
B.	Degrees of freedom	# Joint axes	1	1
C.	Angular velocity	# Joint axes	$\max[\lvert\omega_n\rvert]$	1
D.	Range of motion	# Joint axes	$RoM[\omega_n]$	1
E.	Angular magnitude	# Joint axes	1	$\max[\Sigma_{m=1}^{N} \omega_n]$

RCM during the task. Here we define seven zones. Zone 1 (Z1) ranges from $-20^\circ \leqslant \rho_{12}(t) \leqslant 20^\circ$, corresponding to motions with the highest relative coordination (i.e. neither segment is dominant in the motion). Zones +Z2, +Z3, +Z4 represent progressively less coordinated movements in which segment 1 dominates, with ranges $20^\circ < \rho_{12}(t) \leqslant 40^\circ$, $40^\circ < \rho_{12}(t) \leqslant 60^\circ$, and $60^\circ < \rho_{12}(t) \leqslant 90^\circ$, respectively. Meanwhile, zones −Z2, −Z3, −Z4 represent motion dominated by segment 2, with ranges $-40^\circ \leqslant \rho_{12}(t) < -20^\circ$, $-60^\circ \leqslant \rho_{12}(t) < -40^\circ$, and $-90^\circ \leqslant \rho_{12}(t) < -60^\circ$, respectively.

2.2. Experimental design

A secondary analysis was performed on data acquired from 15 right-handed healthy participants who performed reach/grasp tasks (Fig. 1, (Beckers et al., 2015)). Participants were 23–26 years old (M = 24.4, SD = 1.2), 5 females/10 males, arm lengths 29.2–37.8 cm (M = 33.9 cm, SD = 2.4 cm), and forearm lengths 19.9–29.6 cm (M = 25.7 cm, SD = 2.5 cm). Participants gave written informed consent and the protocol was approved by the MIT Committee on the Use of Humans as Experimental Subjects.

While seated behind a table, participants moved an object from one location to another using their right hand, Fig. 1. In each trial, participants made two movements with distinct trajectories: moving the object from the distal to the proximal location (trajectory 1) and moving the object from the proximal to distal location (trajectory 2). Each trajectory was sub-divided into 5 stages: reach, grasp, transport, release, and return. Kinematics were recorded using a 10-camera motion capture system (Bonita, VICON Inc., USA) at 120 Hz. Eighteen reflective markers were placed unilaterally on the right shoulder, arm, forearm, and hand.

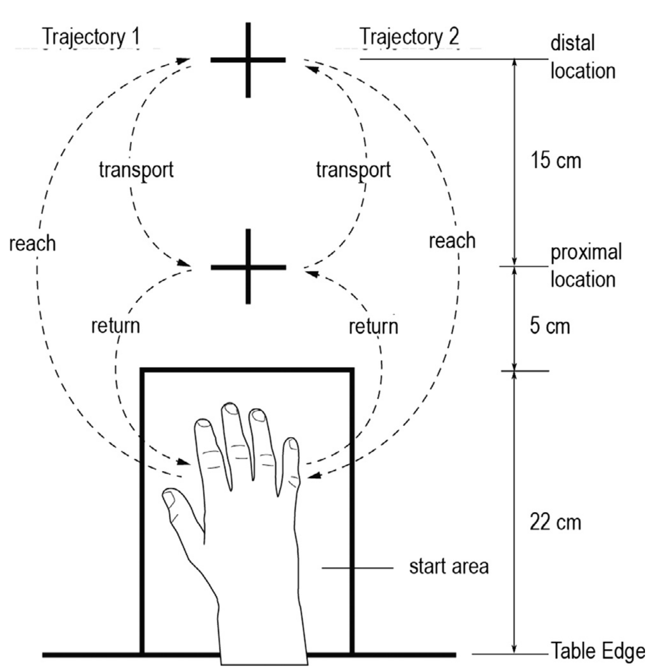

Fig. 1. Task description: participants, seated behind a table, moved an object from the distal location to the proximal location on the table and back. Each trial was divided into two trajectories while interacting with each object. Each trajectory included 5 stages: reach, grasp, transport, release, and return.

Participants performed the task with two objects: a cup (diameter: 6 cm, height: 9 cm, mass: 0.2 kg) and a rod (dimensions and mass like a ballpoint pen). Participants were asked to place the objects on specific marks in one smooth, continuous movement. The pen was placed perpendicularly to the transport direction. Participants grasped one object per trial. A total of four tasks (trajectory 1 and 2 for both the cup and pen) were performed, each with 50 trails (200 total).

2.3. Data analysis

Marker data were processed using Nexus (v. 1.8.5, VICON Inc., USA). The marker position data were filtered using a 6th-order Butterworth low-pass filter (corner frequency at 30 Hz to remove high frequency noise). Joint rotations and translations were determined using inverse kinematics with OpenSim 3.0 (Delp et al., 2007) and the Stanford upper extremity model (Holzbaur et al., 2005). Marker and joint kinematic data were used to determine the start, grasp, release, and end of each trajectory using the movement segmentation methodology in Schot et al. (2010). The start of each trajectory and minimum angular velocity was defined based on Beckers et al. (2015); each trajectory started once the wrist velocity exceeded 3 cm/s (as calculated from a marker on the wrist) and was finished when the hand was completely inside the start area and the wrist velocity was less than 3 cm/s. The grasp event was defined as the moment when the thumb and index fingertip were within 2 cm of the object, the wrist velocity was minimum, and the grip aperture (i.e. closing the thumb and index finger) rate was at a minimum. The moment of release was determined using the same parameters as grasping, but when grip aperture was increasing.

We implemented a 7DoF model of the upper extremity with 3DoF at the shoulder (flexion/extension, abduction/adduction, internal/external rotation), 2DoF at the elbow (flexion/extension, forearm pronation/supination), and 2DoF at the wrist (flexion/extension, radial/ulnar deviation). The RCM was calculated between shoulder-elbow (ρ_{se}), shoulder-wrist (ρ_{sw}), and elbow-wrist (ρ_{ew}) (3 total). RCMs for each trial were time-normalized from 0 (movement initiation) to 1 (movement completion). Each normalization parameter in Eq. (1) and Table 1 were calculated individually for each participant and all 200 trials. The normalization parameters of maximum angular velocity and RoM for each joint axis, as well as the maximum angular velocity magnitude were determined using the OpenSim results.

To analyze the effect of normalization scheme and trajectory stage, the RCM for all three joint pairings and five normalization schemes was extracted at discrete time points associated with the 5 trajectory stages: (A) 50% reach, (B) grasp, (C) 50% transport, (D) release, (E) 50% return.

2.4. Statistical analysis

Statistical analysis was performed using SYSTAT 13.1 (Systat Software Inc., USA). Due to the non-normal distribution of the data set, non-parametric Kruskal-Wallis (KW) tests were performed to assess main effects of our hypotheses. To evaluate the effect of normalization scheme (hypotheses 1) and the effect of trajectory stage (hypothesis 2), 5 values of RCM corresponding to stages A-E (listed above) were selected from the time-series data for each of the 5 normalization schemes, for a total of 25 "norm-stage" groups. The effect of norm-stage on RCM was evaluated by performing a separate KW test for each combination of object (2 levels, cup/pen), trajectory (2 levels, trajectory 1/2), and joint comparisons (3 levels), for a total of 12 tests.

To evaluate the effect of the object grasped (hypothesis 3), $\hat{t}_{\pm Zn}$ for the 7 coordination zones was considered for both objects (cup and pen), for a total of 14 "object-zones," pooling both trajectories together. The effect of object-zone on $\hat{t}_{\pm Zn}$ was assessed using a KW test for 3 of the 5 normalization schemes (Table 1A-C) for each of the 3 joint comparisons, resulting in 9 total tests. The same tests were performed to assess the effect of trajectory (hypothesis 4), however, $\hat{t}_{\pm Zn}$ was considered for both trajectories 1 and 2, for 14 total "trajectory-zones," pooling objects instead of trajectories.

The False Detection Rate controlling procedure (Benjamini and Hochberg, 1995) was implemented to address the multiple omnibus tests performed $(p_i < \frac{m_0}{m} * 0.05)$, where m is the total number of tests performed and m_0 is the number of false null hypotheses prior to the correction. When significant main effects were observed, the Dwass-Steel-Critchlow-Fligner post-hoc test containing embedded correction methods (Dwass, 1957) was performed.

3. Results

A time-series representation of the shoulder-elbow RCM during the four tasks performed with each of the five normalization schemes is shown in Fig. 2A-D. Shifts in RCM between negative and positive values during the time-series are indicative of switching between dominant limb segment. RCM time-series for shoulder-wrist and wrist-elbow are provided in Supplemental Material.

3.1. Effect of normalization and trajectory stage on the relative coordination metric

Norm-stage had a significant effect on RCM in all twelve test cases. Fig. 3 highlights shifts in shoulder-wrist RCM based on the selected stage and normalization during trajectory 1 while grasping a cup. Figures for the remaining joint comparisons (shoulder-elbow and elbow-wrist) and three tasks (trajectory 1 pen and trajectory 2 cup/pen) are provided in Supplemental Material. Post-hoc tests revealed several significant differences between norm-stage groupings. For a given normalization scheme there were significant differences in RCM between stages. For a given stage there were significant differences in RCM based on the normalization scheme implemented.

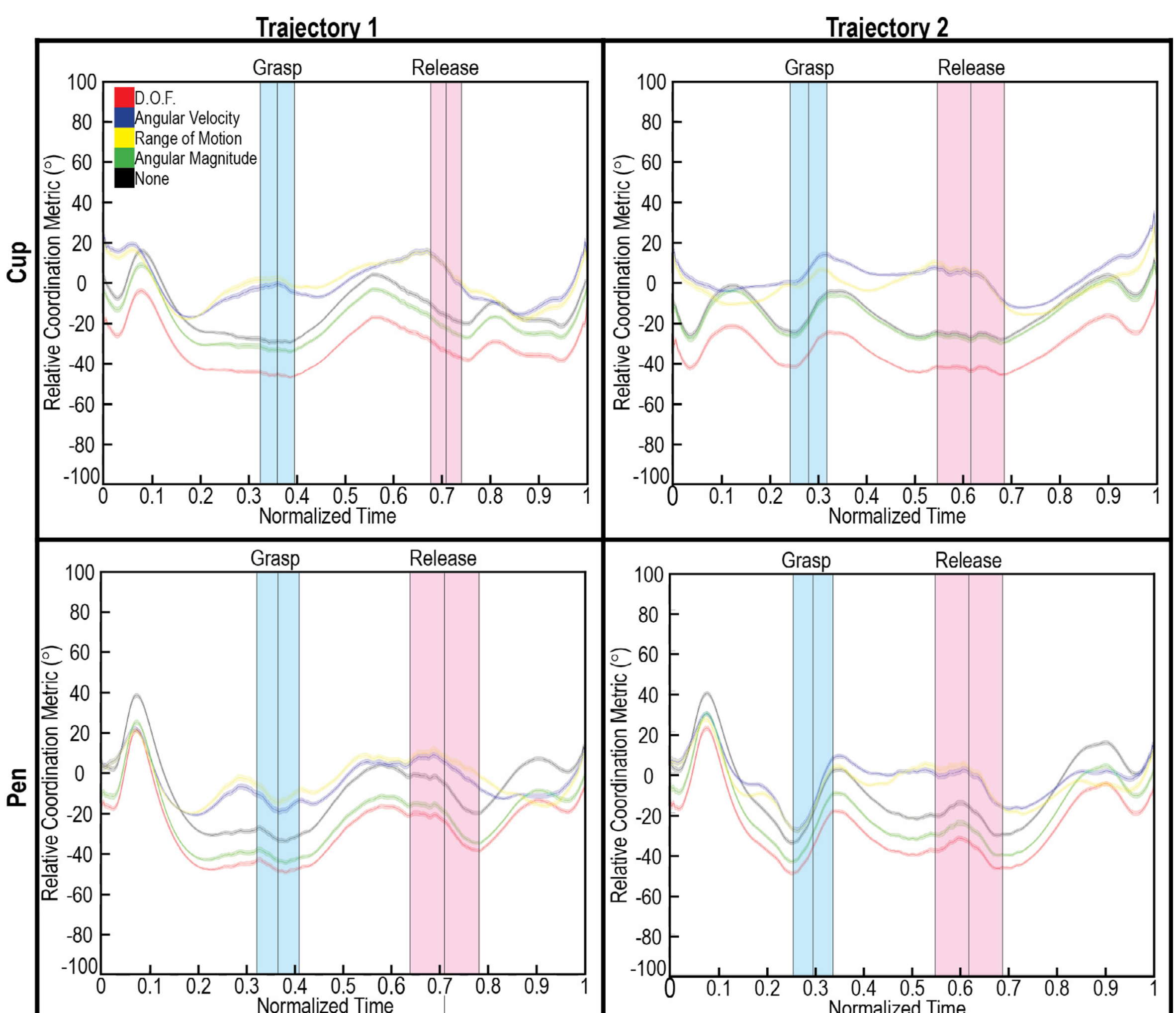

Fig. 2. Time-series shoulder-elbow relative coordination metric: a time-series representation of the RCM between the shoulder and elbow using all five normalization schemes presented in Section 2.4. $+\rho_{se}$ is representative of shoulder dominated motion, while $-\rho_{se}$ is representative of elbow dominated motion. Shaded regions represent the locations of grasp (blue) and release (red) ± standard deviation. Shaded regions around each normalization scheme represent ± standard error. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

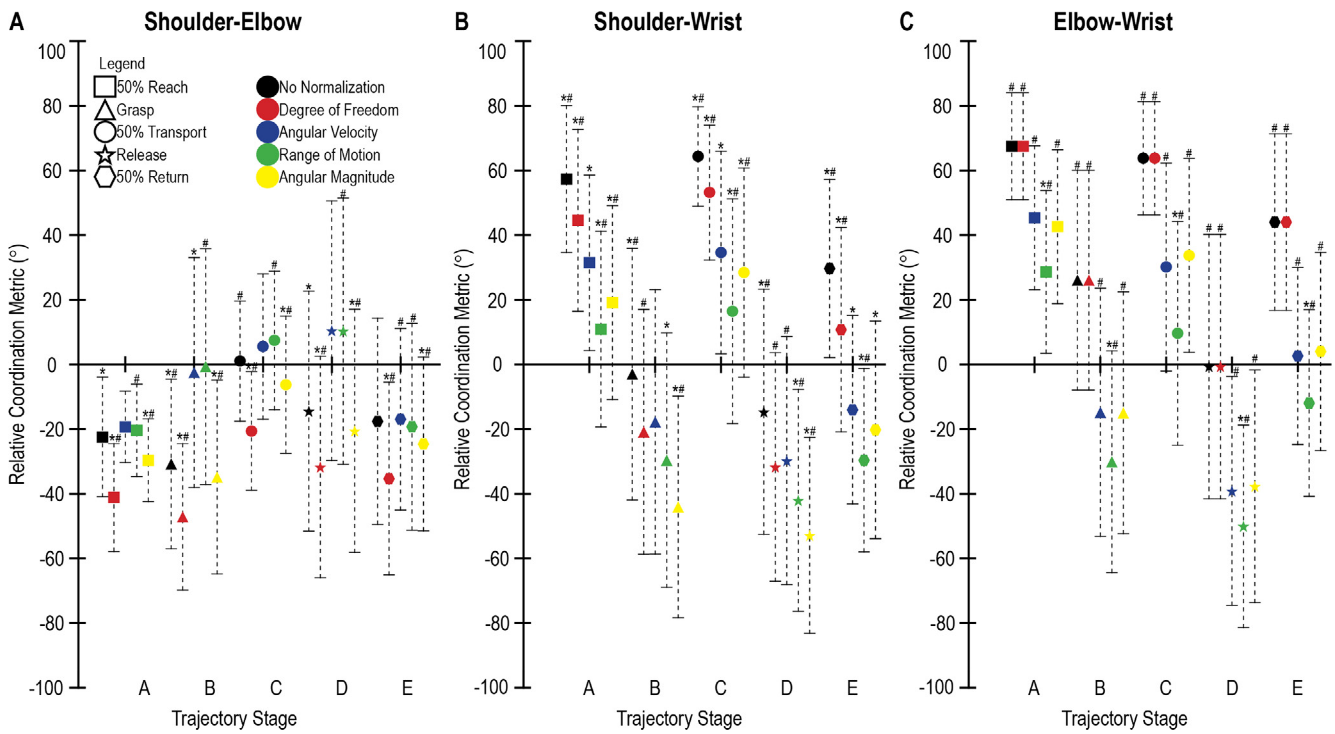

Fig. 3. RCM by normalization scheme and trajectory stage during trajectory 1 when grasping a cup. The five stages tested were (A) 50% of reach, (B) grasp, (C) 50% of transport, (D) release, (E) 50% of return. *Indicates that the selected RCM norm-stage was significantly different from all other normalization schemes at that stage. #Indicates that the selected RCM norm-stage was significantly different across stages for that normalization scheme. More significant differences were present, but not shown here for simplicity.

3.2. Effect of normalization and object on $\hat{t}_{\pm Zn}$

Object-zone had a significant effect on $\hat{t}_{\pm Zn}$ in all nine test cases, Figs. 4 and 5. When normalizing by angular velocity, Figs. 4G-I and 5G-I, post-hoc tests revealed less time spent in each successive zone ($\hat{t}_{Z1} > \hat{t}_{\pm Z2} > \hat{t}_{\pm Z3} > \hat{t}_{\pm Z4}$) for both objects and all three joints evaluated. $\hat{t}_{Z1}$ was greater for the pen than the cup for both shoulder-wrist and elbow-wrist RCMs, opposite for the shoulder-elbow. $\hat{t}_{-Z2} > \hat{t}_{+Z2}$ when comparing the shoulder-elbow while grasping both objects and shoulder-wrist while grasping the pen. Meanwhile, $\hat{t}_{+Z2} > \hat{t}_{-Z2}$ for both elbow-wrist comparisons and shoulder-wrist when grasping the cup. The other two normalizations revealed inconsistent trends between joint comparisons.

3.3. Effect of normalization and trajectory on $\hat{t}_{\pm Zn}$

Trajectory-zone had a significant effect on $\hat{t}_{\pm Zn}$ in all nine test cases, Figs. 6 and 7. When normalizing by angular velocity, Figs. 6G-I and 7G-I, post-hoc tests also revealed less time spent in each successive zone ($\hat{t}_{Z1} > \hat{t}_{\pm Z2} > \hat{t}_{\pm Z3} > \hat{t}_{\pm Z4}$) during both trajectories; these results were consistent for all three joint comparisons. There was no difference in $\hat{t}_{Z1}$ between trajectories 1 and 2 when comparing the shoulder-wrist and elbow-wrist. Shoulder-elbow $\hat{t}_{Z1}$ was significantly greater during trajectory 2 than 1. The other two normalizations examined revealed inconsistent trends between joint comparisons.

4. Discussion

This study introduces and assesses a new metric, the relative coordination metric (RCM), for quantifying non-cyclic, non-constrained coordination based on body segment angular velocity. Qualitative, visual observation of gross motions might categorize certain motions as coordinated, but differences in joint characteristics (DoF, RoM, etc.) might imply that motions are quantitatively uncoordinated when not normalized appropriately. For example, let joint 1 have more DoF than joint 2. With more DoF, joint 1 can move across greater RoM than joint 2; therefore, it can potentially accelerate to higher maximum angular velocities than joint 2. However, joint 1′s higher angular velocities compared to joint 2 do not imply that the overall motion is uncoordinated. Therefore, biomechanical differences require normalization when evaluating this metric to prevent favoring certain joints. In addition, joint RoMs and angular velocity profiles are also task-specific (Bernstein, 1967; Turvey, 1990). For example, a planar reaching task requires less shoulder flexion than an overhead reaching task. Thus, comparisons of intra-participant coordination patterns should be normalized in a joint- and trial-specific manner. Similar to other motion metrics (i.e. joint angles), RCM should be interpreted with a particular task in mind and normative datasets will be required for clinical usage. While this work finds statistical differences when varying a planar grasp/release task, it is necessary to determine what differences are clinically relevant.

Vector coding and CRP, other metrics for coordination assessment, can be difficult to interpret, especially when trying to make conclusions concerning motor patterns in the time-series domain. RCM is a velocity-based methodology that provides a tool that indicates which body segment is dominant and contributes more to the overall motion at any point in time. While the intuitive understanding of this metric needs to be assessed in user studies, we hypothesize that this velocity-based measure will be more straightforward to interpret. Studies on human manual control show that humans typically have an easier time interpreting and controlling velocity and rate-based methods as the human is required to make fewer mental calculations to predict how actions would affect the position time-series (Wickens and Hollands,

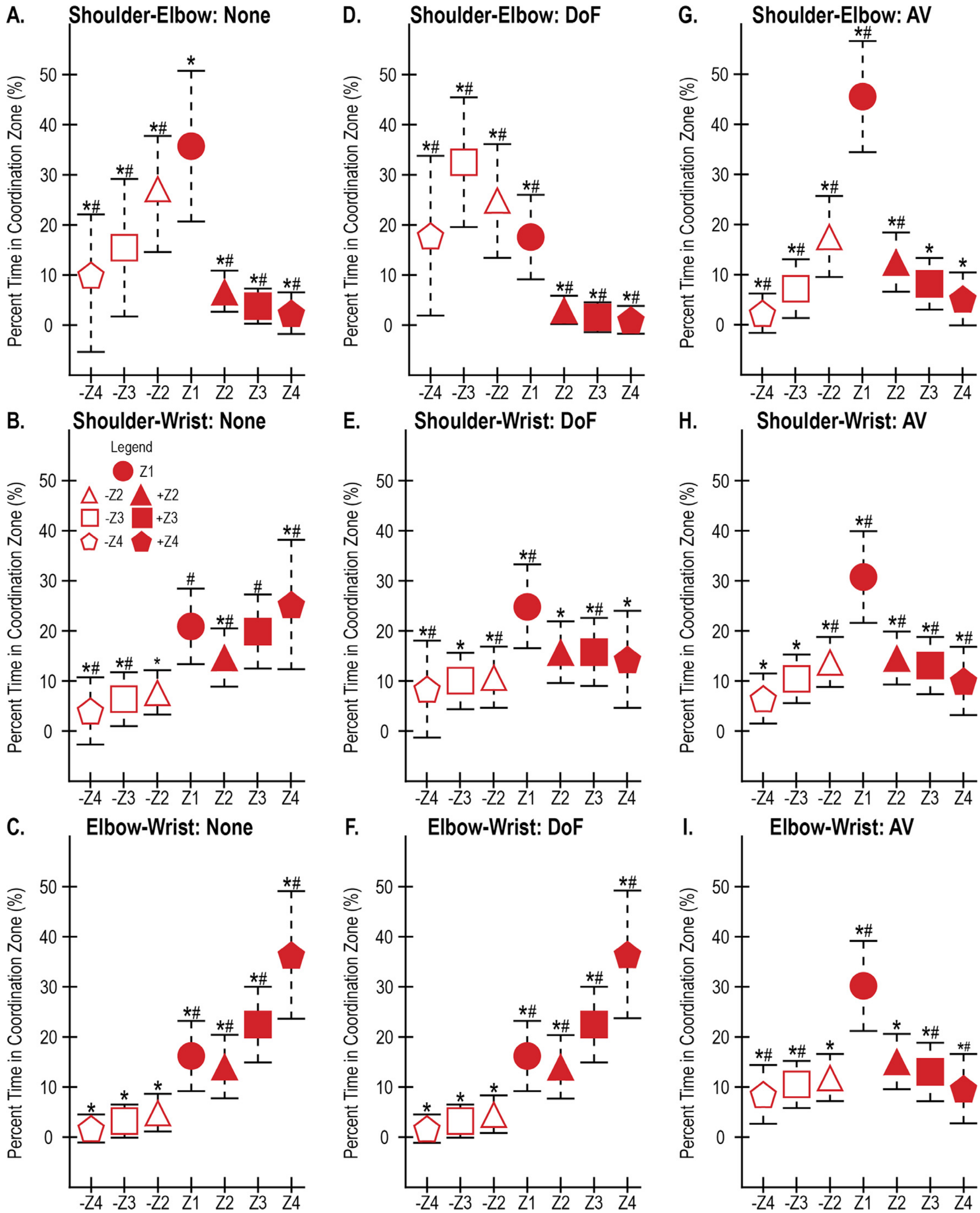

Fig. 4. Percent time in coordination zone when grasping cup by normalization scheme. *Indicates that the selected value was significantly different from all other $\hat{t}_{\pm Zn}$ computed for the cup. #Indicates that the selected value was significantly different from the corresponding $\hat{t}_{\pm Zn}$ of the pen. More significant differences were present, but not shown here for simplicity.

2000). While RCM also transforms the original signal, there are fewer mental calculations required to relate to the original time-series. Therefore, this methodology has potential to more intuitively represent the underlying gross motor patterns. However, additional work is necessary to understand RCM interpretability in clinical settings and during different tasks. While RCM does not currently provide direct knowledge of whether the underlying joint is in flexion or extension, knowledge of the selected task can aid in this disambiguation. Future work will also explore expanding the signal processing to directly provide information on whether the joint is flexing or extending. Relying solely on angular velocity also enables RCM evaluation using wearable sensors, such as inertial measurement units, as the method does not require integration, which can lead to errors over time (Ricci et al., 2016).

These data support Hypothesis 1, which assessed whether the normalization scheme affected RCM, Fig. 3. These data also support Hypothesis 2, finding for a given normalization, the RCM changed across task stage, Fig. 3. The implications of these differences on clinical interpretation can be considered by examining Fig. 2. When normalizing by DoF, it would appear this motion is elbow

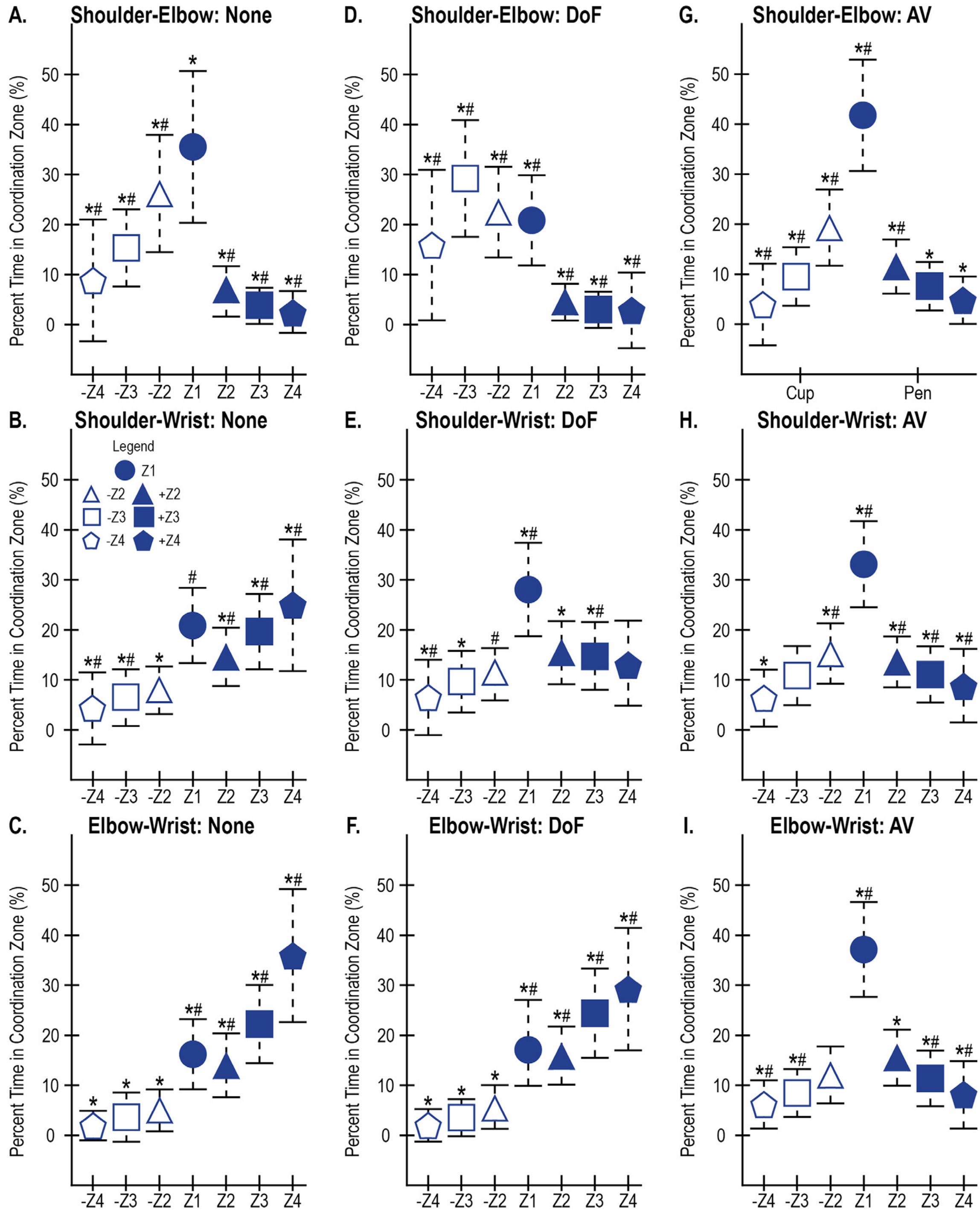

Fig. 5. Percent time in coordination zone when grasping cup by normalization scheme. *Indicates that the selected value was significantly different from all other $\hat{t}_{\pm Zn}$ computed for the pen. #Indicates that the selected value was significantly different from the corresponding $\hat{t}_{\pm Zn}$ of the cup. More significant differences were present, but not shown here for simplicity.

dominated ($\rho_{se} < 0^\circ$) throughout the task. When normalizing by angular velocity or RoM, the shoulder and elbow appear to be moving synchronously ($\rho_{se} \approx 0^\circ$), slightly oscillating between $+\rho_{se}$ and $-\rho_{se}$ depending on the time within the task. These conflicting interpretations could generate different clinical assessments and could affect follow up decision-making on plan-of-care.

Conflicting interpretation of task coordination based on the normalization used also arose when considering $\hat{t}_{\pm Zn}$, Figs. 4–7. Consistent with the time-series interpretation of the data, $\hat{t}_{\pm Zn}$ differed based on the choice of normalization scheme. When interpreting Figs. 4C and 5C (no normalization), $\hat{t}_{Z1} < \hat{t}_{+Z2} < \hat{t}_{+Z3} < \hat{t}_{+Z4}$ indicating that motion was dominated more by the elbow than the wrist. When normalizing by angular velocity, $\hat{t}_{Z1} > \hat{t}_{\pm Z2} > \hat{t}_{\pm Z3} > \hat{t}_{\pm Z4}$, indicating even dominance of both joints. In a healthy population, we would expect that this motion is not dominated by any single joint for this could be evidence of a compensatory mechanism (Geurts et al., 2005; Ward, 2006). Therefore, we would expect $\hat{t}_{\pm Zn}$ is greatest in either Z1 or ±Z2; an ideal metric should align

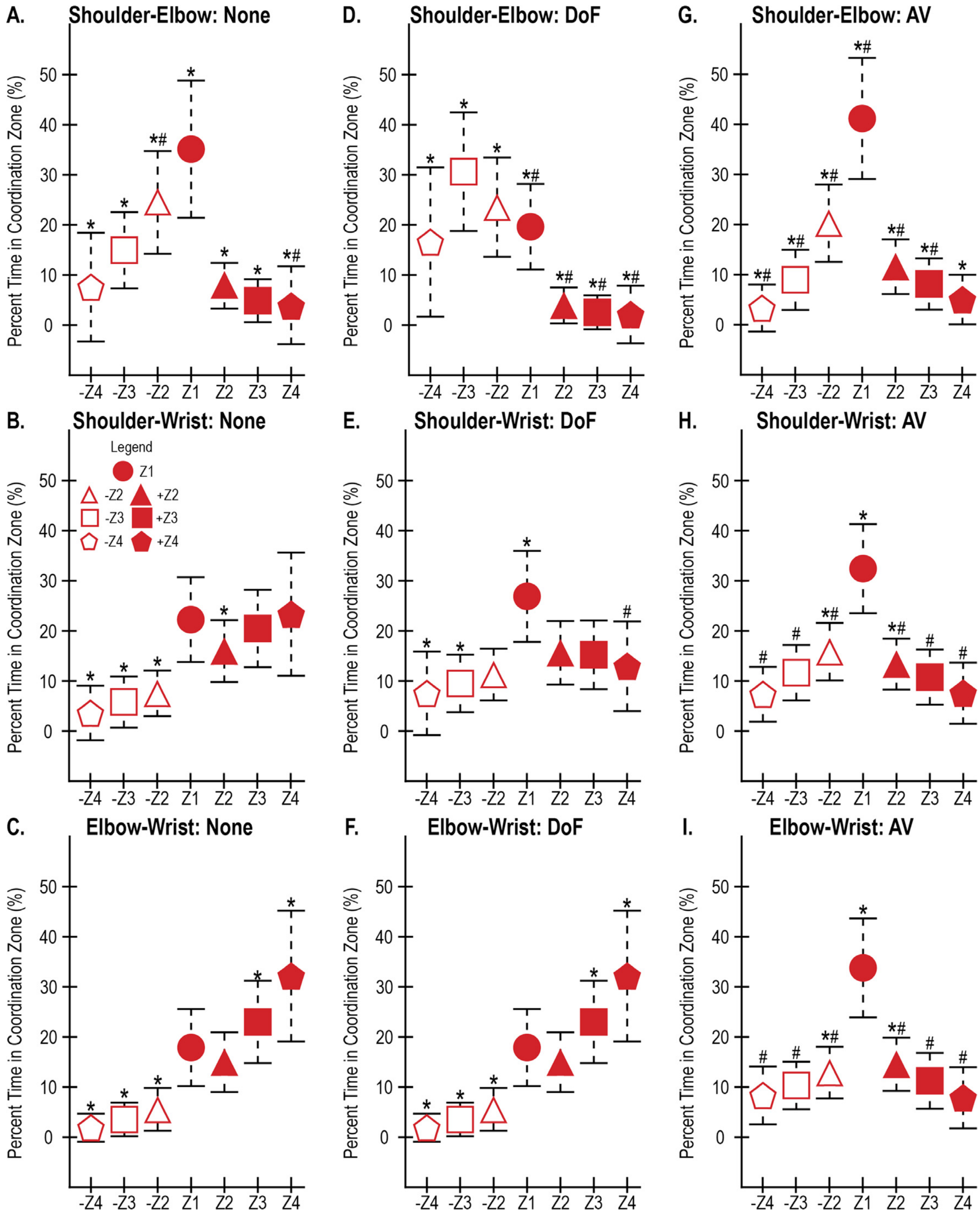

Fig. 6. Percent time in coordination zone during trajectory 1 by normalization scheme. *Indicates that the selected value was significantly different from all other $\hat{t}_{\pm Zn}$ computed for Trajectory 1. #Indicates that the selected value was significantly different for the $\hat{t}_{\pm Zn}$ of the opposing Trajectory 2. More significant differences were present, but not shown here for simplicity.

with this interpretation. Here we find the most appropriate normalization for this task and population is the angular velocity normalization (Table 1C).

Hypotheses 3 and 4 were assessed to determine how sensitive RCM was to kinematic changes arising from the task and environment. Significant differences in $\hat{t}_{\pm Zn}$ were found when interacting with different objects and movement trajectories when using normalizations A-C (Table 1). Interpretation of this task using the angular velocity normalization shows coordinated motions between the shoulder and elbow as $\rho_{se} \approx 0^{\circ}$ within the time-series profiles, Fig. 2, and $\hat{t}_{Z1} > \hat{t}_{\pm Z2} > \hat{t}_{\pm Z3} > \hat{t}_{\pm Z4}$ Figs. 4G and 5G. These results are consistent with previous work that showed linear, coordinated relationships between joint angular velocities during reach/grasp tasks (Soechting and Lacquaniti, 1981; Lacquaniti and Soechting, 1982). While there were statistical differences between both objects and movements, the effect size was small. General trends remain consistent, and these small differences might not be clinically relevant. Therefore, while results from hypotheses 3 and 4 show sensitivity to distinguish between tasks, more work is necessary to understand the effects of different

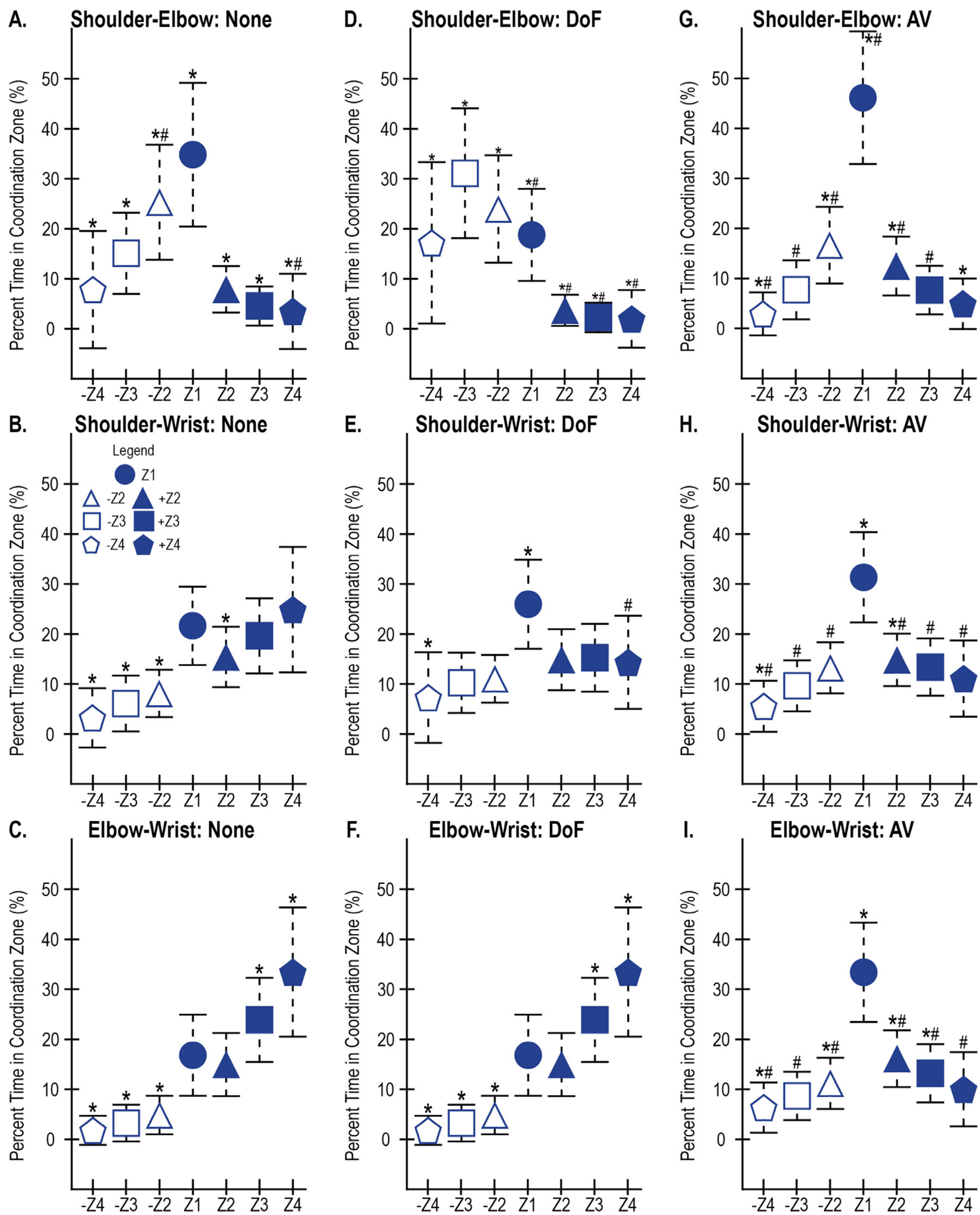

Fig. 7. Percent time in coordination zone during trajectory 2 by normalization scheme. *Indicates that the selected value was significantly different from all other $\hat{t}_{\pm Zn}$ computed for Trajectory 2. #Indicates that the selected value was significantly different for the $\hat{t}_{\pm Zn}$ of the opposing Trajectory 1. More significant differences were present, but not shown here for simplicity.

tasks and environmental constraints on RCM, and to define clinically relevant differences for decision-making.

While normalization by the angular velocity was appropriate for this task and population, it remains to be determined if in other contexts there are normalizations that are more suitable. If specific motion patterns are desired, normalizing by the desired motor behavior instead of normalizing by parameters recorded during the task might be more clinically relevant. A strategy-based normalization could allow clinicians to visualize how patients move relative to these preferred motions. While the current work presents a method that could be used directly for a planar reaching task, more work is necessary to understand which normalization schemes are applicable to a wider range of scenarios, which would enable increased applicability across clinical protocols. As stated previously, RCM value does not infer good or bad coordination; this conclusion arises from synthesizing the RCM, patient's abilities, task performed, and clinician needs. Further, this metric is limited in that it does not inform on the neural control mechanisms that drive the musculoskeletal response, but quantifies the kinematic patterns.

Future work will apply RCM to evaluate upper extremity coordination in a broader set of tasks and patient populations. The usability of this metric will need to be validated with clinicians to understand practical implications when integrated into both tele-rehabilitation systems and clinical settings for assessing patient performance and disease progression. RCM will also need to be validated against CRP and vector coding to understand its applicability to cyclic motions. RCM also shows potential applications in other fields, such as coordination analysis in athletics and performance evaluation of prosthetic devices.

5. Conclusion

We define a new metric to help quantify coordination for clinical application in rehabilitation. RCM addresses some limitations of current coordination measures as it is applicable to discrete motions and uses velocity-based measures. Using RCM to evaluate the coordination patterns of a grasping task in a healthy population, we demonstrate that RCM can discern between different planar reaching tasks. We also show that the interpretation of RCM results can be affected by the implemented normalization. Future work will expand analysis of RCM to different tasks and patient populations to further validate RCM in clinical applications.

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Conflict of interest statement

The authors have no conflict of interest to disclose.

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jbiomech.2017.08.008.

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