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Kinematic Specification of Intention in Full-body Motion

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Abstract

Kinematic specification of dynamics (KSD) states that full-body kinematic patterns of daily activities are reflective of a person's plans, goals, and intentions. Furthermore, it has been shown that observers of those activities are well attuned to differences between those kinematic patterns. However, despite a substantial body of research on the identification of intentional motion, it is not yet clear what the essential kinematic information is required to perceive the intention from the kinematic pattern. Therefore, we analyzed four different intentional full body motions (sit-to-stand transitions: stand, press-stand, press-sit, and reach-up), to determine the essential kinematic information that differentiates them. We utilized principal component analysis (PCA), linear mixed models, and hierarchical multinomial logistic regression to create two predictive regression models that allow us to successfully identify and distinguish the four intentional motions.

Keywords: Intention Recognition; Kinematic Specification of Dynamics; Sit-to-Stand Transition; Point-Light Displays;

Introduction

Activities that people perform in their daily lives are reflected in a person's full body kinematic patterns (Johansson, 1973). Moreover, human observers can easily perceive even small differences in the patterns of a person's motion profile (Ansuini, 2005; Becchio, Manera, Sartori, Cavallo, & Castiello, 2012; Richardson & Johnston, 2005). It has therefore been argued that the information humans derive from another person's biological motion profile can be used to establish successful coordination with others (Pezzulo, Donnarumma, & Dindo, 2013; Sartori, Becchio, Bara, & Castiello, 2009) and with intelligent machines, such as robots (Vernon, Thill, & Ziemke, 2016).

Kinematic Specification of Dynamics

In order to study biological motion, Johansson (1973) created the first point-light displays by attaching small lights to his participants and limiting the exposure of his camera recording to capture only those lights. Johansson called these recordings point-light displays and discovered that when he placed the lights on key joint centers, observers of the displays could identify that the moving points represented a person performing a specific action.

Runeson (1994) framed the findings behind point-light displays in his principle of kinematic specification of dynamics (KSD). The KSD principle postulates that because movement kinematics are lawfully related to the dynamics that produce a movement, the movement specifies the dynamics from which it arose. In other words, the relations among a person's joint centers and joint angles specify the action that they are performing.

Specification of Action Capabilities

Overall, kinematic information has been shown to be remarkably rich. For example, point-light displays of an actor pretending to lift a heavy box are noticeably different from displays of the actor actually lifting a heavy box (Runeson, 1994). Furthermore, observing the kinematics of a person can not only specify the action that is being performed, it can also carry rich information about the action capabilities of the observed person. For example, Ramenzoni, Riley, Davis, Shockley, & Armstrong (2008) have shown that after observers view another person walking, they become more accurate at estimating the walker's maximum reach-with-jump height. Additionally, after watching another person walk while wearing (unseen) ankle weights, observers are sensitive to reductions in the walker's maximum reach-with-jump height caused by the additional weight. These findings indicate that a person's general movement pattern provides sufficient information to make an educated judgment of a person's action capabilities.

Specification of Intention

Although it is evident that people can distinguish another person's activities based on the kinematic structure of the displayed motion, there has been some debate about the richness of KSD in terms of social interaction and intentions. In general, it is hypothesized that the intentionality as reflected in human motion can be used to understand another person’s action plans. Thus, one’s own actions can subsequently be adjusted in response to this understanding and smooth action coordination can be executed (Becchio, Sartori, Bulgheroni, & Castiello, 2008). However, Jacob & Jeannerod (2005) argued that the kinematics involved at the start of a chain of movements might not reflect the end goal of that chain of movements, meaning the kinematics might not accurately reflect the intention. They proposed a thought experiment involving the story of Dr. Jekyll and Mr. Hyde; the two identities belong to the same person, but the former is a renowned surgeon who performs surgeries on anesthetized patients. The latter is a dangerous sadist who performs the same hand movements on his non-anesthetized victims. Jacob & Jeannerod argued that if someone were to witness one of the two identities reaching and grasping for a scalpel, then it would be impossible to specify the social nature and intention through the grasping motion.

Several studies were performed in response to Jacob and Jeannerod’s thought experiment and found evidence against their claim. Ansuini, Giosa, Turella, Altoè, & Castiello (2008) showed that prior intention shapes kinematics by measuring prior-to-contact grasping kinematics for reach-to-grasp movements performed toward a bottle filled with water. By comparing hand shaping across tasks involving different subsequent actions such as pouring the water into a container, throwing the bottle, and moving the bottle from one spatial location to another, the authors demonstrated how prior intention in grasping an object strongly affected the positioning of the fingers, the duration of the reaching, and the contact phase of the movement. Becchio et al. (2008) performed a similar experiment investigating differences between grasping an object to move it to another location and grasping an object to hand it to another person. The velocities and shapes of participants’ hands for both the opening and closing phases of the grasping movement were significantly different between the two conditions, as well as the trajectory of the movement during the passing phase. While Becchio and colleagues demonstrated that movement kinematics differ based on the social or operational intention, Manera, Becchio, Cavallo, Sartori, & Castiello (2011) showed that observers can also differentiate between distinct reaching intentions. They presented point-light displays of different grasping movements including a slow grasping movement, a fast grasping movement, a grasping movement with the cooperative intention of passing an object to another person, and a grasping movement with the competitive intention of grabbing an object before another person. With only access to the kinematic information of the initial forward movement, observers were able to accurately classify which of the four actions was being presented 72% of the time, indicating that the observed kinematic patterns may be used for action coordination during joint activities (see also Sartori et al., 2009).

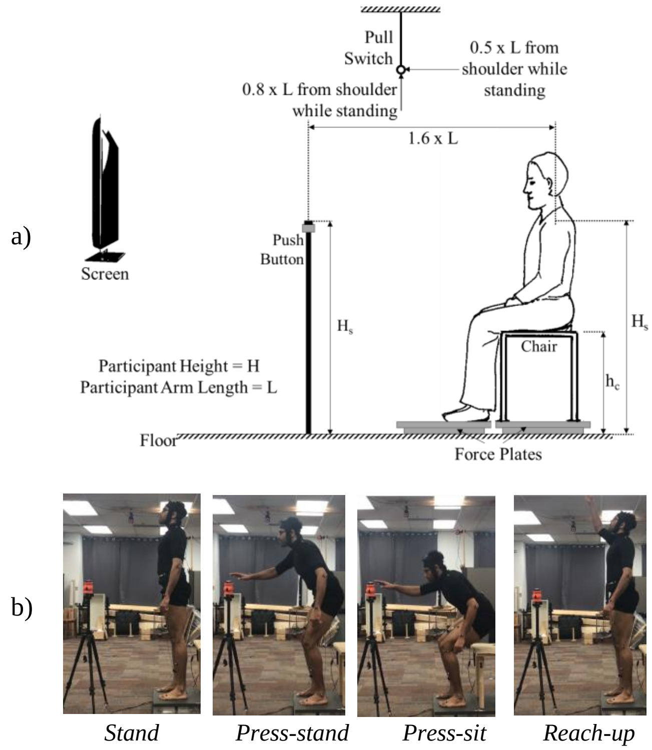

Figure 1: a) Experimental setup for data collection as established and published in Patil et al. (2018). b) Intentional sit-to-stand transitions.

Kinematic Specification of Action and Intention

Although it has been shown that one's movement kinematics provide the information necessary for another person to identify one’s action capabilities and intentions, the informational basis for this ability has not been identified (though see Ansuini, Cavallo, Bertone, & Becchio, 2015). Therefore, in the current study, we adopted a similar approach to Weast-Knapp et al. (2019) who used Principal Components Analysis (PCA) to decompose the kinematic data of walking movements to isolate the informational basis for an observer trying to perceive a person’s action capabilities. However, rather than focusing on the informational basis to estimate a person’s action capabilities, here we explore a different type of full-body movement (sit-to-stand transition, STS) that was executed with different intentions that altered the basic STS motion (see Figure 1b) in order to identify the essential kinematic information of a full-body motion with varying intentions. To gain insight on how people can perceive intention from motion, we must first confirm if the essential kinematic information is different between the motions. If the differences exist, the next goal will be to confirm that humans can extract the same information. Therefore, this paper tackles the first goal of clarifying the essential kinematic structures for STS intentional motion.

Method

In order to enable the analysis of intentional motion, we utilized one subset of a larger data set that was originally collected in context of understanding joint angle variations for exoskeleton control (Patil et al., 2018). The data subset was taken from a healthy, 28-year old male participant.

Setup and Procedure

In order to induce four different intentional STS transitions, a setup was created by Patil et al. (2018) as shown in Figure 1a. A button was placed in front of participants at the shoulder height while sitting and 1.6-times the arm length from the shoulder. A pull switch was positioned above the participant at a height of 0.8 times the arm length and at a distance of 0.5 times the arm length from the shoulder while standing. Motion data was recorded using a 20-camera 3D motion capture system (Motion Analysis Corporation, Santa Rosa, CA). A 29-marker set based on the Helen Hayes body marker placement protocol (Kadaba, Ramakrishnan, & Wootten, 1990) was used to track the motion. A screen was positioned at eye level in front of the participant to provide instructions for the specific trial. Every trial started with the participant sitting at a stool (height 45.72 cm) without any hand or back rests.

The participants were shown a “ready” signal on the screen and, after 3 seconds, the instruction to perform any of four randomized tasks marked the go-signal. The participants performed 100 trials of four intentional STS transition tasks (25 trials per intention): *stand* - the participants were asked to stand up at a comfortable speed without any intention of subsequent activity, *press-stand* - the participants were asked to stand up from the chair while pushing the button in front of them and finish standing up; *press-sit* - the participants were asked to stand up from the chair while pushing the button in front of them and to then immediately sit back down; *reach-up* - the participants were asked to stand up to pull on the switch above their head and after pulling the switch finish standing up. For all trials, the participants were instructed not to use their hands to push down on the chair or their thighs during STS and not to lift their feet from the heel or toes during the trial. The participants were allowed to take breaks whenever they felt fatigued. For the purpose of the current analysis, we included the first four trials of each performed intentional sit-to-stand transitions within the data subset.

Data Analysis and Results

Determining Essential Principal Components

Seven of the original 29 markers (corresponding to the head, right shoulder, right elbow, right hip, right knee, right ankle, and right hand) were selected to form a simple sideview configuration of each motion with the right side of the body represented. We cut off each time series using the furthest point forward in the motion of the hip marker as shown in Figure 1b. This served to truncate the movement to the initial intention-expressing forward portion of rising from a seated position and excluded the stand-to-sit backwards transition. In the future, we plan to use this motion data to explore how human observer respond when viewing it. The Y and Z coordinates of the recorded 3-dimentional motion data were used to perform a Euclidean transformation which provided one value for each marker for each frame of the data set (cf. Weast et al., 2019). The data was then submitted to PCA via R (*base package: prcomp*). PCA is a statistical tool that allows for the reduction of high-dimensional data with the goal of revealing hidden structure in the underlying relationship between variables. For example, previous research has utilized PCA to uncover the most important factors contributing to variation in movement kinematics in gait (Vallery & Buss, 2006), juggling (Post, Peper, & Beek, 2003) and even the movements of cooperating actors (Ramenzoni, Riley, Shockley, & Baker, 2012). Here, we used PCA to reduce the seven-marker data set to a subset of principal components (PC) that captured the dynamics of the kinematic movements. We decided to use PCA rather than machine learning techniques, as we are interested in which joint centers hold the essential kinematic information to differentiate the motions. Though machine learning can help determine the presence of differences and classify each motion, it will not offer insight as to which body segments participate in providing the structure that differentiates movements. Subsequent analyses were performed on this subset to identify the activity of key markers for discriminating between intended movements.

We completed 16 PCA analyses, one per STS motion file (4 intentions × 4 repetitions). Each PCA analysis yielded a **7** (markers) × **7** (PC dimensions) matrix of coefficients, as well as a vector of the amount of total variance accounted for by each PC. The variance vectors were used as criteria to reduce the original data to those PCs that (1) accounted for at least 10% of the total variance in the motion pattern, and (2) provided sufficient variation between intentional movement profiles to be a useful candidate for future discrimination. PC1 and PC2 reliably met criteria (1), suggesting that the data could be reduced to the first two PCs without much loss in information. To determine (2) we submitted the percent explained variance of each PC to a linear mixed effects model (R package: lme4) with intention as a fixed effect and instance (each intentional motion was performed four times) as a random effect. For the sake of brevity, we only report the *F*-tests (Satterthwaite’s degrees of freedom method) for overall significance of the models. Only models for PC1, $F(3,12) = 47.49$, $p < .001$, and PC2, $F(3, 9) = 54.51$, $p < .001$, were significant, suggesting that the amount of explained variance for both PC1 and PC2 differed by intentional movement. For the remaining PCs this relationship was non-significant, supporting our choice to further analyze PC1 and PC2.

Elimination of Non-significant STS Markers in PC1 & PC2

Having reduced the data to the first two PCs, two additional sets of linear mixed model analyses (7 per PC1 and PC2; 14 total) were completed to establish whether the PCA coefficients for each marker systematically varied as a function of the intentional motion.

Table 1. Results of linear mixed model for STS markers on PCs 1 and 2

Marker	Model PC1	Model PC2
M1 (Head)	$F = 86.10, p < .001$ *	$F = 4.82, p = .03$ *
M2 (Shoulder)	$F = 100.44, p < .001$ *	$F = 9.37, p = .004$ *
M3 (Elbow)	$F = 8.52, p = .003$ *	$F = .57, p = .65$
M4 (Hip)	$F = 132.40, p < .001$ *	$F = 19.64, p < .001$ *
M5 (Ankle)	$F = 3.10, p = .08$	$F = .09, p = .96$
M6 (Knee)	$F = 1.07, p = .41$	$F = .08, p = .97$
M7 (Hand)	$F = 3{,}132, p < .001$ *	$F = 2.86, p = .10$

** candidate markers*

Again, intentional motion was entered into the model as a fixed effect with instance as a random effect. The purpose of this series of analysis was to further reduce the dimensionality of the data by identifying candidate markers, whose activity might be used to build a parsimonious model for predicting the intended motion. In short, we sought to determine *which markers* might qualify for submission to a predictive model for intention, as well as *how few* may be used to build a model that reliably discriminates between the intentional movements.

As can be seen in Table 1, the analysis on PC1 revealed that the coefficients corresponding to markers M1, M2, M3, M4, and M7 varied systematically as a function of intentional motion; repeating this analysis for the coefficients in PC2, we found significant systematic variability for markers M1, M2, and M4. These sets of markers provided a list of variables to enter into subsequent regression analysis for PC1 and PC2.Table 2. Results of linear mixed model for STS markers on PCs 1 and 2

Regressing Intention Categories onto Candidate Markers

Using our candidate markers, we performed two hierarchical multinomial logistic regressions (one for each PC) to determine which combination of markers was most parsimonious in reliably discriminating between the intentional movements. For the analysis along PC1, a single marker per hierarchical step was loaded into the regression model in order from largest to smallest PCA coefficient mean. This resulted in a statistically significant model containing markers M7 (hand) and M3 (elbow), which improved the likelihood of determining the corresponding intentions, above and beyond the null (chance) model, as well as all models formed by prior steps in the analysis (see Table 2).

Table 2. Summary of model results for hierarchical multinomial regression for STS markers in PC 1. Only models that yielded a significant improvement are reported.

Step	Variables Entered	df	Likelihood Ratio	*p*
1	**M7**	42	35.81	< .001
2 *final*	**M7 + M3**	39	7.85	.049
	M7 = hand, M3 = elbow			

We followed an identical method for PC2, hierarchically entering each marker into the regression model beginning with the marker possessing the largest PCA coefficient mean. The resulting model was statistically significant, containing M1, M2, and M4, and improved the likelihood of determining the corresponding intentions, above and beyond the null (chance) model, as well as all models formed by prior steps in the analysis (see Table 3).

Table 3. Summary of model results for hierarchical multinomial regression for STS markers in PC 2.

Step	Variables Entered	df	Likelihood Ratio	*p*
1	**M1**	42	6.37	< .001
2	**M1 + M2**	39	13.10	.004
3 *final*	**M1 + M2 + M4**	36	14.88	.002
	M1 = head, M2 = shoulder, M4 = hip			

Examining Improved Accuracy from Model 1 to Final Model

Finally, we compared the accuracy in intention categorization for each of the regression results by calculating the predicted probabilities derived from the fitted values of the Step 1 and final models. For brevity, we report the predicted probability of the true (correct) intentional movement given the PC coefficients for each marker. As expected, we observed significant improvement in predictive probabilities from the first to the final models. For both PC1 and PC2, the predicted probabilities of the final model that corresponded to the correct intention was greater than 95%. Moreover, this was achieved using relatively few markers (PC1: 2 out of 7, PC2: 3 out of 7). Our results suggest that, for PC1, hand and elbow marker activity appear to provide the essential kinematic information to differentiate movement categories (see Table 4).

Table 4. Correct predicted probabilities of multinomial regression models using PC1.

	PC 1: Predicted Probabilities	
Intention	Model 1	Final Model
Stand	97.99%	100%
Press-stand	70.20%	97.03%
Press-sit	86.50%	98.70%
Reach-up	58.22%	95.78%

For PC2, the reduction to head, shoulder, and hip suggests that these markers may contain the essential kinematic information to further differentiates movement categories (see Table 5).

Table 5. Correct predicted probabilities of multinomial regression models using PC2

	PC 2: Predicted Probabilities	
Intention	Model 1	Final Model
Stand	44.50%	100%
Press-stand	62.07%	100%
Press-sit	52.35%	99.99%
Reach-up	22.58%	100%

Discussion

We aimed to identify the essential kinematic information available to observers for distinguishing intentional STS transitions.

Overall, the results suggest that, while the four intentional STS transitions (stand, press-stand, press-sit, reach-up) are built upon similar motion profiles, there are distinct differences regarding the essential kinematic information along the first two PCs, which allows for the accurate differentiation of each intention by means of a specific subsets of markers. Analyses of the coefficients in PC1 and PC2 sufficiently capture the majority of the variance attributed to differentiating the four intentional STS transitions. Additionally, the stratification of specific markers within the two PCs allows us to specify (and differentiate) the essential kinematic structure of each intentional motion. This provided the opportunity to formulate regression models that were capable of accurately predicting intention, above and beyond chance level. Both predictive models allowed for the classification of each intentional STS transition with 95-100% accuracy.

Thus, within each PC, there exists essential kinematic information that can be extracted from the time series of similar, yet distinct, intentional motions. Each marker in the final model, can then be understood as *one of the essential communicators of intention* for each STS transition. In turn, the variation in coefficients indicates *how* each marker contributes to the overall movement pattern of each intention.

For example, analyzing PC1 showed that the majority of variance in the motion data can be explained by the markers reflecting the arm motion (i.e.: elbow and hand marker). Considering that the arm motion differed significantly across intentions (e.g. reaching up vs. reaching forwards), this result is consistent with expectations. Subsequently, analyzing PC2 indicated the presence of additional essential kinematic information in the head, shoulder, and hip markers, which distinguishes suprapostural differences in the kinematics of the full-body motion.

Ultimately, our results reinforce empirical findings showing that humans are capable of visually distinguishing different intentional motion patterns (c.f. Ansuini, 2005; Becchio, Manera, Sartori, Cavallo, & Castiello, 2012; Pezzulo, Donnarumma, & Dindo, 2013; Sartori, Becchio, Bara, & Castiello, 2009) by revealing the essential information that defines and differentiates the kinematic structure of intentional motion.

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