Quantifying Coordination in Human Dyads via a Measure of Verticality

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ABSTRACT

Working towards the goal of understanding complex, interactive movement in human dyads, this paper presents a model for analyzing motion capture data of human pairs and proposes measures that correlate with features of the coordination in the movement. Based on deep inquiry of what it means to partner in a motion task, a measure that characterizes the changing verticality of each agent is developed. In parallel a naïve human motion expert provides a qualitative description of the features and quality of coordination within a dyad. Analysis on the verticality measure, the cross-correlation of verticality signals, and deviation of those verticality signals from the trend over time, provides quantitative insight that corroborates the naïve expert's analysis. Specifically, the paper shows that, for four samples of dyadic behavior, these measures provide information about 1) whether two agents were involved in the same dyadic interaction and 2) the level of "resistance" found in these interactions. Future work will test this model over a larger dataset and develop human-robot coordination schemes based on this model.

CCS CONCEPTS

• **Human-centered computing** → **Empirical studies in interaction design**; **Empirical studies in interaction design**; • **Applied computing** → *Performing arts*;

KEYWORDS

motion-capture, robotics, partner, interaction, coordination, dyad

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1 INTRODUCTION

Human movement is a complex physical phenomenon, full of the richness of contexts, interactions, and variations. In particular, the intricacies of interactive movement raise many research questions, including the manner of nonverbal communication between a pair or dyad performing a task together. In something as simple as moving a table across a room, two individuals communicate through the movement of their bodies in addition to the forces applied on the table and the floor. In partner dance, this communication channel is even more nuanced. When dissecting interactive human movement, we seek to identify properties describing and characterizing these interactions.

A number of studies have been conducted on dyadic interactions. For example, analyzing the making and breaking of symmetry of the head (mirror symmetry) during conversations showed to be a meaningful element of communication when modeled with a dynamical system [5, 7, 8]. Clinicians found that understanding micro-movements using kinematic recordings could allow them to classify dyadic interactions of people with social difficulties more quantitatively [29]. Additionally, movement as an important design aspect in human-computer interaction prompted a course on embodied interaction, formalizing the applications for many movement aspects [11].

Categorizing the large variety of movement can draw analogies from studies that look for parameterizations of other large datasets. The search for a parameterization of images using thermodynamic principles such as energy and entropy drew many parallels between the physical intuition of thermodynamics and properties of the image, revealing measures that reflected natural versus urban images [26]. An interactive online dance work allowed researchers to better understand the interactions between the audience and the work and develops kinesthetic empathy as a parameter in movement representations [10].

Machine learning and neural networks can be used to abstract away the complexities of interaction by training models with examples. Gaussian Mixture Models (GMM) of Interaction Primitives model nonlinear correlations between different movers [12, 18]. Task-parameterized dynamical systems combined with learning allowed a robot to learn a collaborative task after observing a pair of humans performing the same task [24]. A GMM trained with examples of two humans interacting recognized new actions and generated responses of a virtual character [13]. Learning from demonstrations, a virtual dancer developed an internal model of a human dancer's movements using Artificial Neural Networks (ANN) and Hidden Markov Models (HMM) and reacted to some movements from a human dancer [19].

Haptic feedback, a way to measure the forces a user exerts on an interface, is another tool used to understand interactive motion. A dancing robot adjusted the length of its stride based on haptic feedback from the physical connection between robot and human [27], and male and female partner dancing behavior was synthesized based on haptic interactions and stride length [14]. A

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co-manipulation task of a dyad moving a table, characterized by the forces applied by their hands, was used to explore correlations between the various task parameters and the the performance of the pair, including comparisons to minimum jerk trajectories [20].

Motion capture tracks a set of points on a human over time during a movement, producing a skeleton animation that reduces the complex, high degree-of-freedom system of the human body to a finite set of approximately 30 rotating and translating points in 3-D space. Although motion capture does have its limitations such as how "natural" the movements recorded are [30], it is less encumbering than having physically attached sensors. Motion capture can capture many more degrees of freedom than haptic sensors but are limited by neglecting any interactive forces present. Applications have been developed to analyze a human's movement using motion capture and control virtual dancers [6, 28]. Additionally, motion capture data was used to identify key features quantitatively in tango dancing that experts had previously linked to stylistically correct movements [4]. An interactive tango application used motion capture to allow for feedback between two dancers and their music [9]. Motion capture was also used to categorize movement in terms of valence and arousal parameters to classify motion by emotion [17].

This paper describes our analysis of a few examples of interactive motion through existing motion-capture datasets by characterizing the changing verticality of the subjects and tracking how that verticality relates to the coordination between the subjects through a correlation metric. Section 2 gives an extended discussion of partnering that was used to develop the metrics presented here. Section 3 introduces a verticality measure that is used to characterize four samples of dyadic interaction in Section 4 and compare between the samples in Section 5. Finally, Section 6 summarizes the contribution of the paper and points to future directions of exploration.

2 DISCUSSION OF PARTNERING

Within distinct dance styles, interactive motion seems to demand accord between partners on the appropriate conventions for negotiating movement. For example, if two people are moving together within the context of a social dance party, they will likely be moving in a way that is significantly different than if they are moving together in the context of a competitive dance event. For ease of (non-verbal) communication, the partnering agents will agree about which physical cues are meaningful and what constitutes an appropriate response.

This agreement may be prescribed by following the accepted conventions of a particular movement form, all of which place distinct constraints on aesthetic values (i.e. bending and straightening the legs in a waltz versus keeping them soft in a jive [16], or de-emphasizing the line of the body [22]). Decisions are made in real-time by each party based on interpreting physical actions they direct at one another. The quality with which weight is shifted, individually and in coordination with others, seems to be an integral component to the success of the expressed intention, regardless of whether the movement is extemporaneously generated or previously choreographed.

Before defining particular aesthetic values, it's clear that motion may be evaluated in two ways: kinesthetically for the performers

(a) Screenshot from a pair performing Petite Mort with lower resistance within the interaction [3]. The dancers are Roberto Bolle and Greta Hodgkinson performing at Stars of World Ballet Gala Concert, Teatro alla Scala, Milan, Italy in 2006.

(b) Screenshot from a pair performing Petite Mort with higher resistance within the interaction [2]. The dancers are Johan Inger and Elke Schepers performing at Lucent Danstheater, The Hague, Netherlands in 1996.

Figure 1: Examples of varying resistance between two different dyads performing the same movement from Petite Mort. The choreography is by Jiří Kylián, and the music is Wolfgang Amadeus Mozart's Piano Concerto No. 21 in C Major Andante.

and visually by observers. In certain cases of coordinated movement, partners must evaluate movement both visually and kinesthetically. It is interesting to note that coordinated interaction with a partner is dependent on a certain level of trust, in terms of the physical intimacy of touch and proximity, as well as the positions that are compromising physically (such as a lift).

Thus, it seems there are consequences at stake if agents are not aware of the ways they influence each other physically. This assumes, of course, that agents want to level with their partners. Explicitly misleading an agent, while beyond the scope of this paper, is nevertheless a contentious thought when considering how our smallest actions influence and are interpreted by partners. The fact that there might be consequences within the act of moving with others opens up an ethical dimension of understanding weight.

At its simplest, this may be expressed as understanding the physical relationship between weight, anatomic structures, and trust. For example, physically sensing the position of one's pelvis in space relative to that of one's partner, including rotation (toward or away from one's own body), tilt (up or down), and the surrounding muscular activation. Outside of technical anatomy and physiology, one major question that emerges is how this subtlety can be captured and expressed?

The quality with which one resists the force of a partner can reveal valuable insight about the other's position and weight distribution, creating an opportunity to move together in more distinct and nuanced ways. While high levels of tension and resistance may limit mobility, it is less obvious that a subtle understanding of oppositional forces is often the secret to beautiful partnering. In accurately evaluating the level of resistance of one's partner (physically, through a form of feedback, and visually, through a form of feedforward), one can create more controlled patterns, including higher lifts and faster turns.

This is especially evident in the screenshots from different pairs of dancers performing the same choreography (Petite Mort). These images, captured at the same instant in the music, display clearly the effects of differing resistance in a cooperative movement. The first couple executes a supported penchée (standing split) with each dancer on their own and has lower resistance in the movement (Figure 1a). The second couple executes the same position, but with a visual opposition in the movement, corresponding to a higher level of resistance (Figure 1b). The latter couple creates a different artistic expression. One could argue that the latter is a more believable partnership, given that each dancer is communicating their position to the other, as well as relying on the body of their partner to interdependently support balance and control.

Our study attempts to look at visual cues of basic coordinated tasks to make sense of which parameters may be at play. Clearly, the way each dancer distributes weight through their center is crucially different in these two examples. However, motion capture data of this area of the body is difficult to collect. In [25], reflective markers were surgically implanted in spinal vertebrae in order to gain some insight. Our measure will need to access broader, gross movement of the shape evolution of each partner. Thus, we look to the vertical alignment of the spine to monitor, through a low dimensional signal, bodily interactions in a dyad pair.

3 DESCRIPTION OF METRIC

In this section, we will describe the dataset, introduce our model from the motion capture data, and demonstrate how we calculate a one-dimensional verticality metric.

3.1 Description of Dataset

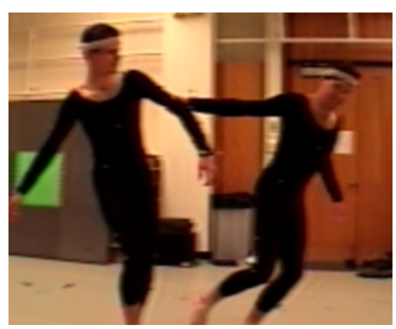
We analyzed four trials of motion capture data from the Carnegie Mellon Motion Capture Database [1]. Each of these datasets was of one person pulling another across a room, with contact point as either the hand or elbow (screenshots shown in Figure 2). However, we visually saw differences in the way the maneuver of pulling was executed, differences that we sought to capture quantitatively. To test our observations, we sent the four videos to a Certified Movement Analysis (CMA) to determine what an expert, qualitatively, saw as differences in the motion profiles.

The expert was instructed to comment on the four videos. Without further prompting, the expert used the word "resistance" to

(a) Hand 1

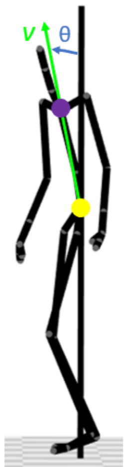
(b) Hand 2

(c) Elbow 1

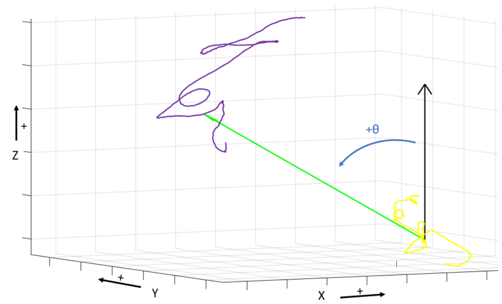


(d) Elbow 2

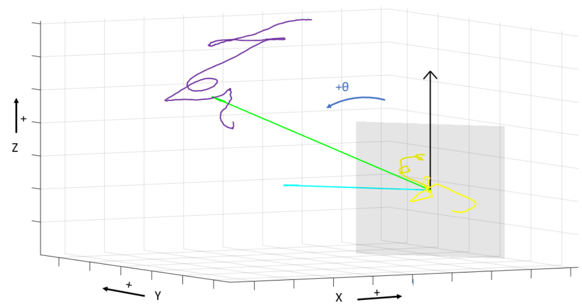
Figure 2: Screenshots from the videos from each of the four motion capture datasets. Classified here by point of contact (hand or elbow), with two videos in each category [1].



(a) Labelled motion capture skeleton



(b) A lowerneck (purple) and root (yellow) signal for a single subject. Also displayed is the difference vector v for a single time step (green) and the z-direction vector in black ($\hat{k}$) and the direction of positive θ.



(c) Indicates the positive direction of the calculated angle θ by computing the plane (gray) spanned by the cross product of v and $\hat{k}$ (light blue) and $\hat{k}$. The positive direction is toward the vector v on the left side of the plane.

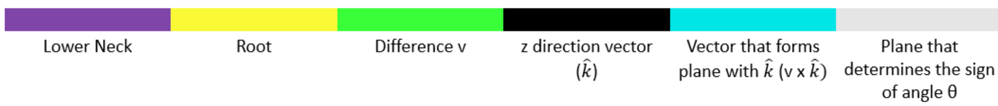


Figure 3: Process from the motion capture data to the angle between the difference vector v and the vertical direction $\hat{k}$

Video	Excerpts from expert comments
Hand 1	Lots of resistance to the pull
Hand 2	Less resistance to being pulled
Elbow 1	More resistance from the [person pulling] initially...but the resistance diminishes over the course of the action
Elbow 2	Little resistance to being pulled

Figure 4: Excerpts from expert comments about 4 interactive motion videos

describe the movements in each of the videos. Table 4 shows excerpts from the comments we received, specifically the portions related to this concept of resistance. For Hand 2 and Elbow 2, the expert described the movement using phrases such as "less resistance" and "little resistance to being pulled." For Hand 1 and Elbow 1, she characterized the movement by "lots of resistance" and "more resistance," but for Elbow 1, the "resistance diminish[ed]" slightly over the course of the action.

This "resistance" parameter that she observed qualitatively is a guiding principle for our analysis in our goal to compute quantitative metrics describing the data. With the four videos (two with hand as the point of contact and two with elbow), we separated the trials by subject. Subject A was the individual pulling, and Subject B was the individual being pulled. The two subjects across the four videos resulted in a total of 8 distinct motion profiles.

The input to our analysis was the raw motion capture data in the `.amc/.asf` format. Using MATLAB functions provided by [21], we converted this data into a set of trajectories: (x,y,z) for each joint. To further simplify the analysis, we focused on the movement of the core: more specifically, how the lower neck joint moved with respect to the pelvis (root) joint (specifically the lowerneck marker with respect to the root marker). For each dataset, we have a root (r) and lower neck (n) signal, both in $\mathbb{R}^3$. A visual representation of the vector v (green), root (yellow), and lowerneck (purple) for a single time-step are shown in Figure 3a superimposed onto a motion capture skeleton.

Each of the four motion capture datasets was of slightly different length, so we first resampled each r and n signal to be of uniform length T using the MATLAB `spline` function. These trajectories were not oriented in any specific way in space, so we next applied a rotation matrix to the signals to orient them in a manner that resembled our intuition about how the motion was carried out. A simple rotation by 90° about the x-axis and flipping the signals from right to left ($r_i = r_{T-i}$ and $n_i = r_{T-i}$, $\forall i = 1, 2, ..., T$) allowed the subjects' direction of motion to be in the positive x-y direction and the vertical direction to be in the positive z direction.

Figure 3b shows a r (yellow) and n (purple) signal as an example. Note that the n signal is rotated counterclockwise about the r signal, so the root and neck signals are not positioned vertically above each other. We do not correct this rotation because for each dataset this offset rotation is different, and we did not wish to hand-label any of the analysis. However, this offset will be accounted for later in our analysisthrough a normalization process.

Next, we calculated a difference signal v which is simply $n - r$ and is the neck signal with respect to the root signal. This captures the three dimensional movements of the individual's torso during the movement and removes any overall translation effects. $v \in \mathbb{R}^3$ for one time step is shown in Figure 3b as the green vector, going from the yellow root signal to the purple neck signal.

3.2 One-Dimensional Verticality Metric

The angle θ is measured with respect to the unit vector in the positive z-direction ($\hat{k}$), shown in black in Figure 3c). Using the relationship between the dot product and the cosine, in Equation

1, we find the angle θ between the vector v and the unit vector in the z-direction $\hat{k}$. When taking the inverse cosine in Equation 2, we ensure that the resulting angle is $0 \leq \theta \leq 90°$. The final step is the normalization of θ to $\hat{\theta}$ by subtracting the mean of θ at each time step from θ to obtain a signal centered at 0 (Equation 3). When performed for each dataset, this eliminates the effects of the different offset rotations and allows us to compare the oscillatory patterns between $\hat{\theta}$ signals.

$$\|\hat{k}\|\|v\| \cos\theta = \hat{k} \cdot v \tag{1}$$

$$\theta = cos^{-1}\left(\frac{\hat{k} \cdot v}{\|v\|}\right) \tag{2}$$

$$\hat{\theta} = \theta - \bar{\theta} \tag{3}$$

Because of the offset rotation explained previously, the magnitude of θ will be positive ($0 \leq \theta \leq 90°$) for all time steps. The positive direction is defined, as shown in Figure 3c as on one side of a plane (gray in the figure) defined as the span of $\hat{k}$ and v x $\hat{k}$ (light blue vector). The offset is different for each dataset, so the magnitude of the positive angle that represents the vertical will be different for each dataset, but characterizing the changes in the angle will show, in all cases, the oscillatory behavior of the individual's torso. Another important point is that approximating the three dimensional vector v with a single dimension will necessitate that changes in verticality in lateral and forward direction are not differentiated.

To compute the correlation between two signals, we used the Pearson correlation coefficient that takes two one dimensional signals as input and outputs the correlation between them [23]. Equation 4 shows the value of the correlation c for two signals, x and y, of length n.

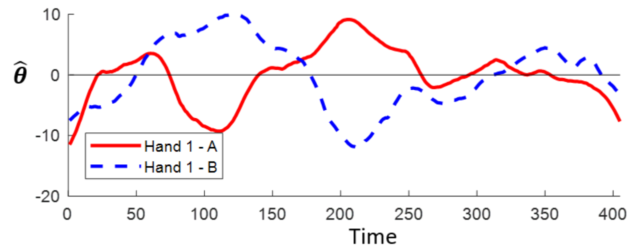
$$c(x, y) = \frac{\sum_1^n (x - \bar{x})(y - \bar{y})}{\sqrt{\sum_1^n (x - \bar{x})^2}\sqrt{\sum_1^n (y - \bar{y})^2}} \tag{4}$$

4 RESULTS FROM VERTICALITY ANALYSIS

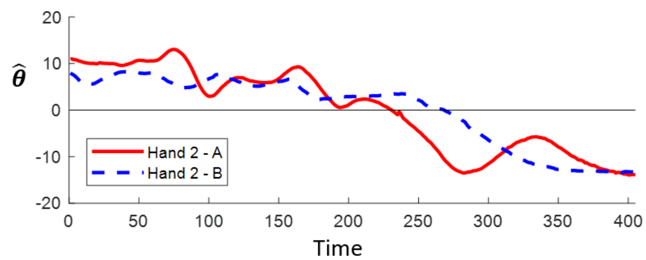
For each of the four videos, we computed the $\hat{\theta}$ signals for Subject A and Subject B and compared the two signals for each video with each other. Figure 5 displays the Hand datasets (the two videos where the attachment point of Subject A to Subject B was Subject A's hand), and Figure 6 displays the Elbow datasets (where the attachment point was the elbow).

The first observation about the $\hat{\theta}$ signals for each subject in the same task (the red solid and blue dashed lines plotted together) is that there seems to be a correlation or anti-correlation between the signals. For Figure 5a and the first half of Figure 6a, the two signals seem to the anti-correlated, with oscillations in opposite directions throughout the movement. In Figure 5b, Figure 6b, and the second half of Figure 6a, the signals seem to be more correlated, with approximately matching shapes.

These observations match the overall structure of the comments made by our movement expert (Table 4). For the Hand 2 and Elbow 2 videos, there was less resistance to the pulling, manifesting in a direct correlation between the $\hat{\theta}$ signals. For the Hand 1 video, there was more resistance, manifesting in an inverse correlation between the signals. The Elbow 1 video is a special case because the movement starts out as high resistance (first half is anti-correlated), but ends as low resistance (second half is correlated).

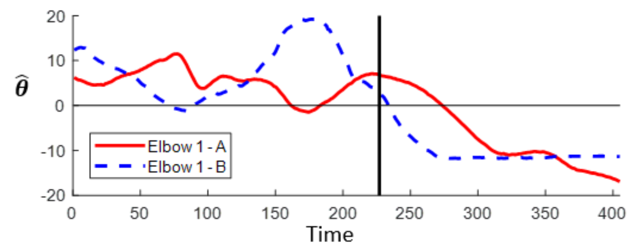


(a) Hand 1

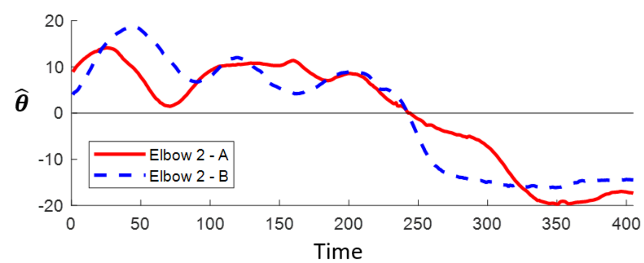


(b) Hand 2

Figure 5: Comparison of the verticality angle $\hat{\theta}$ (in degrees) for the Hand datasets with Subject A (red, solid) pulling and Subject B (blue, dotted) being pulled.



(a) Elbow 1, with the black line indicating the separation between high and low resistance behavior



(b) Elbow 2

Figure 6: Comparison of the verticality angle $\hat{\theta}$ (in degrees) for the Elbow datasets with Subject A (red, solid) pulling and Subject B (blue, dotted) being pulled.

To quantify the correlations between the signals, we computed the Pearson correlation between the signals in each video, values shown in Table 7. To determine the location to split the Elbow 1 signals (shown as a black line in Figure 6a), we found that the maximum negative correlation occurred with the first 227 points and split the signals in two parts according to that line. The table shows a high magnitude of correlation (all above 0.5) between verticality signals of two individuals performing an action together. Additionally, the sign of the correlation corresponds to the comments made by an expert about high and low resistance movements. The positive correlation values represent low resistance behaviors, and the negative correlation values represent high resistance behaviors.

Video	Resistance Level	Expected Sign	Correlation
Hand 1	High	Negative	-0.5636
Hand 2	Low	Positive	0.8577
Elbow 1 (beginning)	High	Negative	-0.8658
Elbow 1 (end)	Low	Positive	0.702
Elbow 2	Low	Positive	0.9038

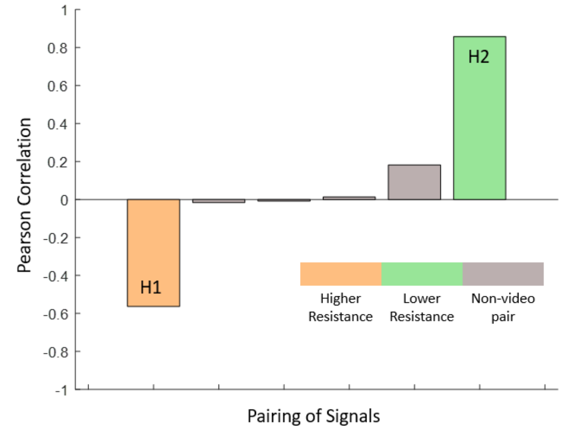
Figure 7: Pearson correlation between $\hat{\theta}$ signals from each dataset. Also displays the resistance level and corresponding expected sign of the correlation. The Elbow 1 dataset is split into the first half (beg) and second half (end).

We would like to determine whether these correlation values actually indicate that an interactive task is being performed. We will define a *video pair* as a pair of signals from the same task (i.e. Hand 2, Subject A and Hand 2, Subject B). We anticipate that the magnitude of correlation between a video pair will be higher than a *non-video pair*, which would be comparing signals extracted from two different videos. For the Hand videos, we compared all possible pairings of the 4 signals (a total of 6 pairings), which resulted in 2 video-pairs (from the two videos) and 4 non-video pairs.

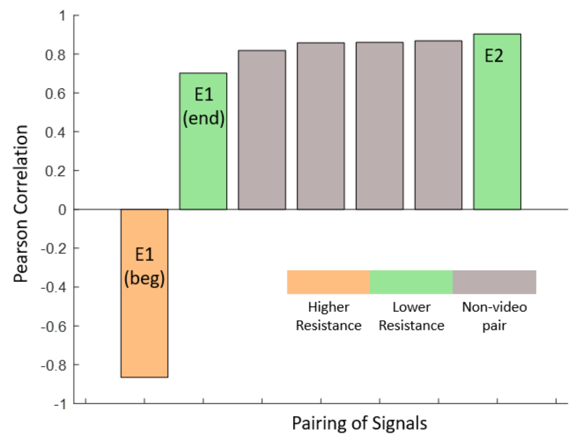
Figure 8a displays all 6 correlation from the Hand pairings from lowest to highest with the two video pairs labeled as H1 and H2. These results match our expectations: the high and low resistance cases (video pairs) have high correlation magnitudes, and all other pairings have low magnitudes. This would indicate that a high correlation magnitude corresponded to coordination in a task, for these cases.

We performed exactly the same analysis on the Elbow videos, but with a total of 7 pairings. We compared each of the 4 signals in pairs to each other, but then replaced the one value from the Elbow 1 video pair with two values (one from each half of the signals).

The results are shown in Figure 8b and do not have the same clear distinction between video and non-video pairs as in the Hand case. In fact, all non-video pairs have high correlations (above 0.8). We hypothesize that this distinction is due to the difference in point-of-contact during the interaction, and the more proximal attachment created less variety in the verticality signals within the Elbow datasets. Despite not being able to distinguish video and non-video pairs by correlation for these cases, we can still differentiate high and low resistance behavior by the sign of correlation.



(a) Correlation of video and non-video pairs for Hand pairings.



(b) Correlation of video and non-video pairs for Elbow pairings.

Figure 8: Correlation of video and non-video pairs for Hand and Elbow signals. The bars are sorted from least to greatest with high resistance (orange), low resistance (green), and non-video pairs (gray) appropriately colored.

5 RESULTS FROM RESISTANCE ANALYSIS

From the results of the correlation calculations, there is a clear difference between the high (anti-correlated) and low (correlated) resistance cases that matches the expert observations of the movements. Another visual difference in the shapes of the signals are the varying height and oscillations between high and low resistance.

To quantify this difference, we performed a statistical analysis of each $\hat{\theta}$ signal. We first found the linear regression by the least-squares method of each signal, shown in Equations 5 and 6, where the Pearson correlation (c) of the time t and $\hat{\theta}$ are used as well as various standard deviation (SD) measures. This gave us a line about which the deviation of the signal was minimal. We then found the standard deviation of the residuals, shown in Equation 7.

This resulting a for each signal quantifies the amount of oscillation occurring about a line that minimizes that oscillation. Figure

10 shows the linear regression for each of the 8 $\hat{\theta}$ signals separated by resistance and point of contact.

$$b = c(t, \hat{\theta})\frac{SD(\hat{\theta})}{SD(t)} \tag{5}$$

$$\hat{\theta}_{est} = bt + (\bar{\hat{\theta}} - b\bar{t}) \tag{6}$$

$$a = SD(\hat{\theta}_{est} - \hat{\theta}) \tag{7}$$

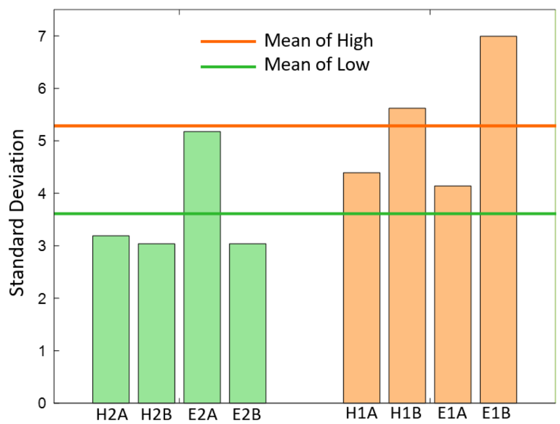
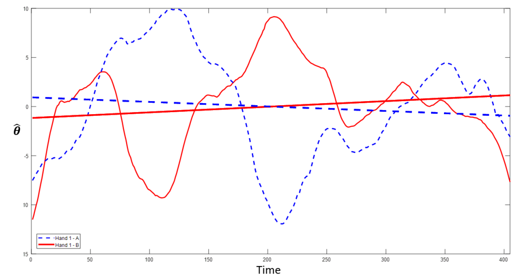


Figure 9: Comparison of the standard deviation of the difference of each signal from its linear resistance, separated by higher (green) and lower resistance (orange). Also pictured is the mean of the each subgroup, which shows the higher mean of the higher resistance group. The labels along the x-axis correspond to hand or elbow (H/E), video number (1/2), and subject (A/B).

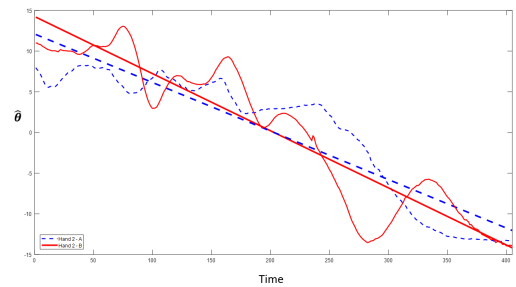
To quantify the visual differences in the verticality graphs of the high and low resistance cases, we computed the standard deviation of the difference of each signal from its linear regression (from Equation 7). Figure 9 displays the standard deviation values separated by low (orange) and high (green) resistance signals. In this analysis, we have classified Elbow 1 as higher resistance for simplicity. Additionally, the mean of each group is plotted onto the figure in the appropriate color, showing that the mean standard deviation of the high resistance signals is higher than that of the low resistance signals. This agrees with our observations of the greater oscillations in the high resistance cases that quantify the differences observed by our expert about these movement pattern.

6 CONCLUSION AND FUTURE WORK

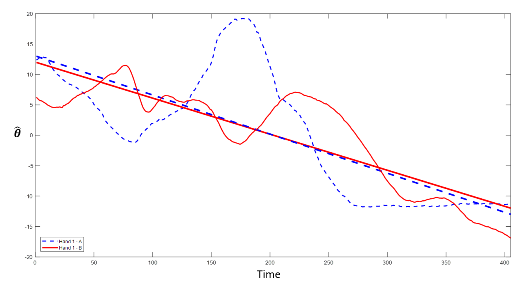
Movement of two physically connected humans is a complex activity involving several degrees of freedom, many of which motion capture does not encompass. However, we propose a model that, for our current dataset, proves to be descriptive. Our results show a correspondence between computations performed on the reduced degree-of-freedom model of the changing verticality of the subjects (a correlation metric) and features of the dyad coordination. Both whether or not two individuals were engaged in the same task with hand-to-arm contact and the quality of "resistance" in the partners were considered. Our analysis corroborates the naïve observations a movement expert. Happily, our analysis does not depend on the



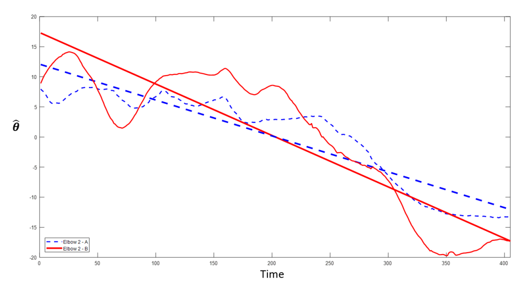
(a) Hand 1



(b) Hand 2



(c) Elbow 1



(d) Elbow 2

Figure 10: Linear Regression for each of the 8 $\hat{\theta}$ verticality signals with Subject A (red, solid) pulling and Subject B being pulled (blue, dashed). Classified here by point of contact (hand or elbow).

type of task, so the verticality metric can be easily tested on a variety of other tasks and contexts to determine other conclusions that can be drawn from this measure.

In future work, we aim to tackle a few limitations of our current results. First, the number of datasets is low, and to broaden the implications of our results, extending this analysis to a greater quantity of data is needed. The quality of the datasets is another crucial factor. These "pulling" datasets are from an online database created for broad generic use. Recording our own data after giving individuals (including experts in partner work) clear instructions may create a more pronounced distinction between the high and low resistance cases. Lastly, there are other parameters, like resistance, of interactive motion that have previously only been characterized by qualitative observation and can possibly be quantified by a similar methodology. Understanding the way humans interact allows for greater parameterization of the movement domain and can allow for a richer movement generation.

The phenomenon of resistance is a key feature in the context of human-human interaction. A better understanding of what this phenomenon entails opens up opportunities for more nuanced interactions that involve touch, including in social and medical settings. In dance, choreographic structures may place particular restraints on how dancers interact with one another, which may inhibit them learning to interact in ways that are particularly efficient, effective, or otherwise optimal.

Using motion capture technology to examine nuanced interaction paradigms like resistance may lead us back to bodily inquiries, creating technology that prioritizes and improves human-human interaction. As technology improves, we are provided with more opportunities for human-robot interactions. For example, some Apple products make use of haptic technology, an interface which prioritizes a certain level of nuanced understanding of pressure and resistance. The more we understand about how we interact with objects, and other moving agents, the greater the potential for more nuanced interactions [15].

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