Structurally Rich Movement: Measuring Movement for Empirical Psychology and Examining the Dynamic Complexity of Affect Regulation in Behavior

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DEDICATION

To my family; my late grandparents, my grandfather, Robert, my sister, Jackie, my mother, Tammy, and my father, Michael.

To Kali, my love.

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ABSTRACT

Movement not only permeates human life, but structures dimensions of experience. Phenomenological theory points to the dynamic congruency of movement and emotion, via the body schema, as shaping affectivity. For psychology, this calls for an understanding of behavior beyond being discrete events, but also manifesting kinetic melodies. Yet there is a gap in existing methodology for empirically studying the three-dimensional characteristics of human movement continuously across segments of the body. A potential line of research in this area, implicit affect regulation capacities, was described to inform the selection of instrumentation, measurement, and calculations of dynamic structure that would, theoretically, best measure movement for this and likely other purposes.

Regarding instrumentation, an active motion capture system based on the Xbox Kinect and iPiSoft software was selected. Regarding measurement, rotational kinetic energy was identified from the biomechanics literature to meet this requirement. Calculations of dynamic structure focused on a measure of complexity, or structural richness, called multivariate multiscale sample entropy (MMSE).

The agreement between the active system and a gold standard passive motion capture system was assessed on two components of rotational kinetic energy, rotational magnitude velocity and segment length, and on dynamic structure calculations. Two MFA actors (one male and one female) and a male professor of theater performed a total of 20 movement sequences, which were concurrently measured by the two systems.

The active motion capture system satisfactorily estimated dynamic movement in agreement with the passive system. It also estimated summary measures in high agreement with the passive system. Calculations of dynamic structure were in satisfactory agreement as well. Analyses of MMSE calculations from the active system data provided initial evidence that this process could characterize movement complexity as structural richness, perhaps describable as the body moving as a coherent whole over time. The instrumentation and data processing procedure described in this project can be used to validly measure dynamic movement in psychology. Limitations of the study and future directions in the research and methods are discussed.

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CHAPTER 1: INTRODUCTION

> In the beginning, we are simply infused with movement -- not merely with a *propensity* to move, but with the real thing. This primal animateness, this original kinetic spontaneity that infuses our being and defines our aliveness, is our point of departure for living in the world and making sense of it...It is in effect the foundation of our sense of ourselves as agents within a surrounding world. But it is even more basically the epistemological foundation of our sense of who and what we are. *We literally discover ourselves in movement.* (Sheets-Johnstone, 2011, p. 117)

Progress in the study of embodiment and embodied cognition has informed much about how one's bodily activity is related to decision marking, semantic knowledge, and perception (Lakoff & Johnson, 1999; Gallagher, 2006; Noe, 2004). In particular, Gallagher's basic insight into the body schema (as opposed to the body image; 1986) has provided for psychology a way to conceptualize the relationship between embodiment and the self. Considering the body as supporting ownership and agency reveals how our temporal embodiment is central to ongoing experience (see Ratcliffe, 2008 on "existential feelings"). Sheets-Johnstone makes the case that movement is so central to experience as whole, that to call cognition "embodied" is merely to apply "a lexical band-aid" to theory (1999, p. 260), as the term obscures how fundamentally the animate body permeates basic dimensions of experience.

As animate movement has emerged as an important dimension of phenomenological understandings of experience, testable claims challenge empirical psychology. While the applications of these theoretical advances and traditions to clinical psychology have yet to be fully worked-through (see Fuchs, Sattel, & Heningnsen, 2010), there remains a clear vacancy in the psychological methodology in the measurement of movement of the whole body over time. While some technology exists that might work well for related purposes, the accuracy of such technology remains untested, the system requires much preparation of participants, and the approach to movement data does not straightforwardly accommodate the needs of basic psychology research or applied clinical assessment (c.f., Burger & Toiviainen, 2013).

There is a vast literature on these topics for the purposes of biomechanics and kinesiology, which cover a whole range of questions. Naturally, there are extensive and highly advanced instrumentation in these fields for the collection, processing, and analysis of kinetic (e.g., energy and force) and kinematic (e.g., velocity and acceleration) variables (Winter, 2009; Robinson, Caldwell, Hamill, Kamen, Whittlesey, 2013). However, there is unfortunately no readymade translation of instrumentation from biomechanics to typical questions and contexts of basic or applied psychology. The physics of human movement is incredibly complex, the instrumentation advanced, and the data processing extensive. For these reasons, if there is to be any sustainable study of movement for the questions of psychology, there must be an accessible, theoretically-derived framework that draws out the most relevant features of biomechanics methodology and describes a validated process.

In this project, I attempt to do just that. To bring relevant measures into focus, I will sketch out a specific line of research that serves as one impetus for studying movement. This sketch brings to the foreground the most relevant features of biomechanics measurement for this kind of research. Following, this project proceeds with the task of establishing the credibility of a candidate instrument and process for studying these features. Hence this study serves as an attempt to establish specific instrumentation, and moreover, a general data collection and processing strategy that feasibly gathers reliable and relevant measurements of dynamic movement.

An Impetus for Studying Movement in Psychology

There have been several forays into the study of movement and spatiality in psychology including proxemics (Hall, 1966), the embodiment of music listening (Luck, Saarikallio, Burger, Thompson, & Toiviainen, 2010), and interactional synchrony (Ramseyer & Tschacher, 2011). Based on work in these fields and on phenomenological theory, there remains open the possibility to characterize movement dynamics as features of personality and self-regulation capacities. Self-regulation is thought to be transdiagnostic feature of psychopathology with core behavioral, experiential, and biological features (Carver, Johnson, Joormann, & Scheier, 2014). Developmental perspectives on self-regulation processes point toward the interactional dynamics of early relationships with primary caregivers as formative for relatively enduring styles of affect regulation (Fonagy, Gergely, Jurist & Target, 2004). Often described as attachment styles, these persist from early developmental context into adulthood (Fraley, Roisman, Booth-LaForce, Owen, & Holland, 2013), and are thought to be especially active during situations of interpersonal threat (Fonagy et al., 2004).

A major theme in attachment research involves describing how highly relational processes that play out in the presence of the primary caregiver transform into further sophisticated processes that can operate in the primary caregiver's absence (Fonagy et al., 2004). This is characterized in a central question: how it is that interpersonal regulation becomes self-regulation? A candidate mechanism for the regulation of affect early in life is the interactional synchrony of the primary caregivers and their child (Isabella & Belsky, 1991). Defined by the coordination of movement between a primary caregiver and their child, this kinematic process has foundational importance for containing and productively expressing the infant's affect (Feldman, 2007). Infant-mother interactional synchrony is a thoroughly kinetic and whole-body phenomenon, reaching to a primary dimension of human experience that the phenomenologist, Sheets-Johnstone, seems to capture with her claim that "movement is our mother tongue" (2011, p. 195).

Several authors have described models which posit automatic and dynamic styles of overregulation, underregulation and optimal regulation of affect, explicitly linking the concept of attachment styles to these affect regulation styles (e.g., Nolte, Guiney, Fonagy, Mayes, & Luyten, 2011). Cassidy proposed such a theory, conceptualizing attachment security as a capacity for open and flexible emotion expression in threatening situations (1994). Alternatively, two insecure attachment styles utilize different maladaptive affect regulation styles in her scheme: avoidant individuals exhibit inhibited emotion expression while anxious individuals exhibit heightened and undercontrolled emotional expression. Evidence suggests that these styles are relatively independent of temperamental proneness to anxiety and are more related to a developed skillfulness (Cassidy, 1994, p. 233). A similar theory has been proposed by Siegel, who stitches together various levels of analysis in his integrative developmental approach to interpersonal neurobiology (2012).

To capture how the complexity of how affect regulation functions in adults, Fonagy, Gergely, Jurist, and Target developed the concept of mentalization, and particularly the achievement of *mentalized affectivity*, which the authors define as “the capacity to connect to the meaning of one’s emotions” (2004, p. 15). They describe two levels of affect regulation that may result in this state of mentalized affectivity. On a primary level, affect regulation is a matter of maintaining a basic equilibrium; on a secondary level, affect regulation involves a process of meaning-making and interpersonal interpretation (2004, p. 95). This secondary level is also often called reflective function, a term with a longer history (Fonagy & Target, 1997) and employed by related lines of research (e.g., Levy et al., 2006). Exploration into how these levels of affect regulation might interact over time remains a methodological and theoretical challenge.

Toward this end, Fonagy, Gergely, and Target suggest that mentalization might be considered skillful process that involves “a self-reflective and an interpersonal component, is both implicit and explicit, and concerns both feelings and cognitions” (2008, p. 793). Related theory about self-regulation has operationalized some of the mechanisms of regulatory control in more concrete terms, as feedback-loop models of biobehavioral subsystems (Carver, Johnson, Joormann, & Scheier, 2014; Carver & Scheier, 2012). Effectively maintaining a primary, though complex, regulation of goals and affect, one might clear an opening for imagination or productive thought.

Kinetic Melodies Gifted with Meaning

Following the suggestion of affect regulation as being a kind of background skill with roots in synchrony with primary caregivers, I contend that skillfulness becomes a useful metaphor for extending our knowledge about the two-personal dynamic model of affect regulation in early childhood into a dynamic one-personal model of the adult personality. Skillful affect regulation seems to develop, in part, through the interactional synchrony of movement, which suggests that the complexity of adult individual affect regulation may also unfold, in part, as a dynamic structure of movement.

Fleshing out the notion of movement as structuring affect regulation remains a difficult, almost intractable problem from a rigidly Cartesian perspective. Pausing a strict delineation between cognition and affect, or mind and body, may allow for alternative approaches to emerge. Theoretical work in phenomenology can provide some foundational comments in support of such an alternative endeavor. In *The Structure of Behavior*, Merleau-Ponty attempts a critique of Cartesian approaches to mind and reductionism in behavioral and gestalt theories of psychology and offers a nuanced understanding of the organism as a living whole (1942/1983). In doing so, he assigns behavior a major role in the ongoing maintenance equilibrium of the organism: “...each organism, in the presence of a given milieu, has its optimal conditions of activity and its proper manner of realizing equilibrium” (Merleau-Ponty, 1942/1983, p. 148). This move highlights an empirical and dynamic perspective on behavior which necessarily departs from understanding behavior exclusively as reactions to collections of specific stimuli.

He describes behavior as not necessarily a “thing,” and neither as an “idea” (Merleau-Ponty, 1942/1983, p. 127), but as a “kinetic melody gifted with meaning” (Merleau-Ponty, 1942/1983, p. 130) or a “form” (Merleau-Ponty, 1942/1983, p. 148). This stance holds that neuroscientific perspectives on behavior need not be restricted to reductive discoveries of parts and subparts, but also need not abandon the investigation of physical processes for the sake of saving conscious experience. This is harmonious with Luria's insight into the "kinetic melodies" of skilled movement through his study of function breakdowns due to lesions in the premotor cortex (Luria, 1973).

Contemporary phenomenological perspectives on movement expand beyond early life and consider movement in circular exchange with emotional experience over time (Fuchs & Koch, 2014), forming a *dynamic congruency* (Sheets-Johnstone, 1999). These works amplify phenomenological insights of Husserl and Merleau-Ponty who observed a rather complex yet primary *temporal* intertwining between expression and behavior - especially in the contexts of affect, self-experience, and interpersonal relating (Husserl, 1977/1931; Merleau-Ponty, 2002/1962). The temporal construction of experiences through movement and emotion might thus be understood as a major factor in the skillful engagement in the world (Dreyfus, 2002).

Measurement of Dynamic Movement

Taking seriously the theoretical importance of expressive behavior, empirical psychology is presented with a methodological challenge. An operationalization of it as dynamic movement stands at the nexus of psychology, biomechanics, and phenomenology. Affect regulation and experience meet body segment rotational kinematics and whole-body systemic dynamics at a juncture where there seem to be great potential for measurement, but without a coherent account of relevant measures to be validated. By analogy, some continuous measures of event-related potentials via electroencephalogram (EEG) have been applied to much success in measuring the continuous neural activity of affect regulation (Amodio, Master, Yee, & Taylor, 2008). Similarly, behavior might be measured as continuous movement.

Such an approach should squarely measure affect regulation as it simultaneously unfolds for the self and in significance for others. The person would be understood as a dynamic, animate system unto themselves; open or closed to interactional synchrony with others, and characterized by systemic and dynamic movement as an active and expressive whole. This perspective becomes less concerned with the directions of body segment rotation than with the fact of movement and the trajectories of movement over.

Some previous work has attempted to document the dynamic features of movement beyond immediate gestural or semantic functions. A striking example is Labanotation, a movement notation system often used to document dance choreography (Guest, 2014). The products of Labanotation function like a sheet of music, using different shapes, symbols, and colorations to indicate the features of a movement sequence. The theoretical approach of Laban has been applied to some models of human movement in psychology research (e.g., Foroud & Whishaw, 2006) and in modelling qualities of animations (the EMOTE Model; Chi, Costa, Zhao, & Badler, 2000). A drawback of assuming a system of discrete descriptions of movement like the Labanotation system, or directly applying Laban's theoretical framework to movement, is that it may not be sensitive to systemic qualities of continuous movement. Instead, it seems that the measurement of movement dynamics as a continuous physical index may more closely describe the operations of movement as a biological phenomenon and provide a productive framework for observing the dynamic structure of affect regulation. Toward this end, biomechanical measurement can effectively track human movement over time (Robertson, Caldwell, Hamill, Kamen, & Whittlesey, 2014). Some research has successfully applied this technology to the study of personality and musical movement, but inaccessibility of such instrumentation makes it less-than-ideal for widespread application in psychology, since relies on specialized expertise, expensive equipment, and affixing many reflective markers (see Luck, Saarikallio, Burger, Thompson, and Toiviainen, 2010). A need for instrumentation in this area remains.

Measurement of Movement in Focus

Measures. One historic convergence of clinical psychology and biomechanics lies in the appreciation of human gait patterns (Jaspers, 1963). In the case of gait there are various measures in biomechanics, like interstride intervals, which capture key aspects of the movement (Mentiplay et al., 2015). However, these measures do not directly apply to the general question of expressive movement, where there is not necessarily a concrete, predictable event like time intervals between walking strides. Instead, the frameworks of general energy and dynamics seem more well-suited approach for the task of measurement. Additionally, any measure should be robust to different forms of movement and contexts -- it should be able to flexibly assay expressive movement in an open-ended fashion.

One destination of measurement is body segment rotational kinetic energy (Robinson et al., 2013). With the whole body as the system of interest, a rotational perspective on body segment movement is most appropriate, where body segments rotate at joints and implies gross movement of the body in space. Kinetic energy provides a scalar of movement, a one-dimensional summary of three-dimensional movement. Not only does this make the interpretation and computation of movement data easier, but it also harmonizes well with neuroscientific methodology, like EEG and fMRI, which are also often processed into scalar values over time.

The calculation of the rotational kinetic energy of a given body segment requires a few indices for calculation: 1) segment mass, 2) segment length, and 3) rotational velocity. Segment mass is estimated through models defining segments as proportions of the total body mass (de Leva, 1996), so its reliable measurement only depends on having the person’s overall mass. A motion capture system can estimate segment length. Generally, segment length is held constant for a given participant and is considered as a one-time set of values applied to calculations conducted on each frame of a movement sequence (Robinson, et al., 2013, p. 63).

This leaves rotational velocity as the primary variable for which validity needs to be established. Rotational velocity is typically described as the change in Euler angles per second, capturing each of the three dimensions of rotation (Robinson et al., 2013, p. 50). A whole-body model, with many body segments, and three dimensions of rotation being modelled for each, culminates into gratuitous data for a generalized description of movement dynamics. If we were to have reliably-measured rotational velocity, we would proceed with the XYZ rotational velocities separately in some calculations before bringing together as kinetic energy (see Appendix A for a description of this process). For the sake of concision and with the calculation of three-dimensional kinetic energy in mind, the current effort turns the three-dimensional rotational velocity into a different one-dimensional scalar: magnitude rotational velocity. This was achieved by taking the Euclidean norm of the three rotational dimensions.

The measurement of human biomechanical data across the whole-body results in multiple channels of body segments – magnitude rotational velocity, in the current case. There are different ways to arrange these multiple channels data. Under the guiding framework of kinetic energy, each of these segments would preferably be described in an individual over time, that is, one channel of data per body segment per recorded movement sequence. These channels could also be summed together to form a whole-body total over time, or in different subgroups, but they could also be kept separate and statistically modelled as a complex dynamic system that moves as a coherent whole over time.

Dynamic structure of movement. Studies in biomechanics have employed algorithms that calculate the variability of movement over time in terms of meaningful structural complexity instead of modelling it away as irrelevant noise (Newell, Deutsch, Sosnoff, & Mayer-Kress, 2006). A family of univariate and multivariate mathematical algorithms, entropy models, quantify such structural characteristics of variability (Goldberger et al., 2000). A univariate measure that seems promising for the measurement dynamic movement is multiscale sample entropy (MSE; Costa, Goldberger, & Peng, 2002). It also has a multivariate counterpart, multivariate multiscale sample entropy (MMSE; Ahmed & Mandic, 2011). These emerge out of the tradition staked by Kolmogorov-Sinai entropy, which describes entropy as mean information richness or the level of description needed to produce a given output (Costa, Goldberger, & Peng, 2002).

Shifts toward appreciating the potential structural characteristics of variability have led to progress in understanding dynamic structure of healthy, optimal performance across human systems. A leading line of research in this effort has demonstrated that optimal heart rate styles are richly complex, while unhealthy styles have been shown to either be highly predictable (e.g., highly regular beats) or highly random (e.g., atrial fibrillation; Costa, Goldberger, & Peng, 2005). Similar models have been applied to discover increases in the dynamic complexity of brain activity among individuals with schizophrenia after taking antipsychotics (Takahashi et al., 2010), to discriminate between fMRI data of young and elderly adults (Sokunbi, 2014), and to characterize the difference between healthy and unhealthy human gait and balance dynamics (Costa, Peng, Goldberger, & Hausdorff, 2003).

Instrumentation. There remains the matter of how to acquire three-dimensional rotational information for the computation of scalar of movement like magnitude velocity in an accessible and reliable way. A procedure and software package that currently exists in the psychology literature is called Motion Energy Analysis (Ramseyer & Tschacher, 2011). This method calculates the frame-by-frame pixel changes on standard two-dimensional digital video plane. It has been used in basic research on the affective atmosphere of interpersonal interactions in experimental settings (Tschacher, Rees, & Ramseyer, 2014) and in clinical research, for example, in studying the effect of a movement-based intervention on negative symptoms in schizophrenia (Gabrusela, Finn, & Fuchs, 2015). This system does not model three-dimensional movement, nor does it capture the movement of separate body segments, so it does not meet the requirements for the current project. However, it has functioned successfully in research as a general indicator of *how much movement* transpires in a region of interest over time, the term of art being “motion energy” (Ramseyer & Tschacher, 2011, p.

286). The degree to which this method might estimate whole-body kinetic energy remains an open question outside the scope of this project, but it does give context for the task at hand.

Passive motion capture systems are standard in the measurement of movement in biomechanics. While they are extremely accurate, they require significant preparation of a single participant with markers and in the modelling of their morphology ‘from the bottom up.’ This process also requires expertise on the part of the experimenter and a large, dedicated space for the sophisticated network of cameras involved. If motion capture is to be smoothly integrated into psychology research on movement dynamics, finding more feasible and more inconspicuous instrumentation is paramount.

An active motion capture system is a promising response in this regard. These systems are active in the sense that they actively fit a human figure to depth data ‘from the top down.’ By nature of actively modelling, these systems introduce an additional layer of estimation into the collection of raw movement data, naturally introducing additional error. Increased error in the measurement of movement dynamics by active systems may be tolerable given accessibility advantages, but only if they can be thoroughly validated. Active systems seem well-positioned for use in research on expressive movement that requires the collection of three-dimensional dynamic data. Where large numbers of participants are frequent, a markerless, active system provides a way to measure the movement of people rather immediately, without applying materials to a participant or having them wear any specialized gear.

Specifically, the Microsoft Kinect system may be able to reliably achieve such measurements while meeting the requirements of research on expressive movement. While the Kinect may not reach the accuracy needed for fine-grained biomechanical questions achievable by passive systems, the accuracy and rate of measurement may be suitable for estimating the spatiotemporal characteristics of movement. While there are several studies on the accuracy of the Kinect version 2 data (e.g., Clark et al., 2015; Geerse, Coolen, & Roerdink, 2015; Mentiplay et al., 2015), it has yet to be established whether this system can viably record a general measure like magnitude rotational velocity in an open-ended fashion, across varied situations that one might reasonably encounter in experimental or clinical psychology. Thus, a study was designed to examine the agreement between the estimates of this active system with a passive system on magnitude rotational velocity in body segments. This study also presents the development of a general procedure for processing movement data and for analyzing the dynamic structure of movement.

CHAPTER 2: METHOD

This study approached the question of agreement through the concurrent measurement of a series of movement sequences performed by three participants. With the active and passive systems measuring the identical scene simultaneously, differences between these systems were due to instrumentation.

Participants

Three individuals participated in this study. Two were actors studying for their Masters of Fine Arts (MFA) in Acting (one male, one female) who performed a series of seven varied movement sequences. The other participant was a professor of theater who specialized in movement training. He performed six sequences of corporeal mime from the training tradition of Etienne Decroux (Decroux, 1985; Leabhart, 1989). All study procedures were approved by the institution's Internal Review Board and all individuals gave written informed consent for participation and video recording.

Experimental Procedure

After the calibration of instrumentation and basic preparation of participants for both movement systems, they were asked to perform a series of movement sequences. The two MFA participants each received identical instructions for movement sequences and performed them in the same order: treadmill walking freely and governed by a metronome, one minute sequences of random and swaying movement, the simulation of an interview procedure, a corporeal mime piece, and a brief walk through the capture area on the ground. These tasks were selected to provide a varied database of samples with widely different properties intended to push the limits of the active system's movement tracking capacities, they also offered ways to explore the dynamic structure of movement. Refer to Table 1 for a summary of these movement sequences.

Movement Sequences for the MFA Actors

Treadmill Walking: Free and Paced Movement

Participants were asked to walk on a commercial-grade treadmill both freely and with their steps paced by a metronome for one minute each. Speed was held constant within the two trails of the participants, but was set to a participant-determined comfortable speed. The metronome, which gave the constant indication of beats per minute (bpm) by a "click" sound, was set at 120 bpm. The two conditions, *free* and *paced* allow for a replication of findings that long-range correlations present in free walking are broken down in metronome-paced walking (Costa, Peng, Goldberger, Hausdorff, 2003; Hausdorff et al., 2001).

Table 1. Movement Sequences

Sequence	Duration Limit	Participant: Female MFA Actor	Participant: Male MFA Actor	Participant: Professor of Theater
Free treadmill	1 min	x	x	
Paced treadmill	1 min	x	x	
Random	1 min	x	x	
Swaying	1 min	x	x	
Mock stress interview	5 min	x	x	
Ground walking	None	x	x	
The Rope	None	x	x	x
Flick of the Seahorse's Tail	None			x
Actions of Agriculture				
Scythe	None			x
Pulling a cart	None			x
Pitchfork	None			x
Sowing seeds	None			x

Random and Recurring Sequences

For further samples of expressive movement with different properties, the MFA actors were instructed to conduct two further movement sequences: *random,* to move around randomly for one minute and *swaying,* to sway in place for another minute. These sequences also served the purpose of providing candidate lower-complexity movements for comparison to natural expression, which was conceptualized to have more structural richness.

Mock Interview

As one planned application of movement measurement to psychology was through a well-defined stress induction paradigm, the Trier Social Stress Test (Kirschbaum, Pirke, & Hellhammer, 1993), MFA actors were asked to undergo the administration of the test for a 5-minute duration in character. In summary, they were instructed to interview as a character of their choosing for a "dream job." The inclusion of this in our experimental procedure allowed for the closest possible test to expectable conditions for the study of movement in an experimental psychology context. It also tests agreement at a longer duration.

Corporeal Mime: The Rope

MFA actors will be asked to perform a prepared corporeal mime piece. In this sequence, the participant moves as if they hand off a rope, which will be referred to as *The Rope.* Expert execution of movement sequence requires the coordinated articulation of all body segments. While giving yet another opportunity to test the accuracy of the system, the inclusion of the sequence also allowed for exploring the sensitivity of the complexity calculations to movement between two students and an expert on the same sequence. Each participant performed the sequence three times during their recording.

Ground Walking

To assess the active system's ability to capture kinematics at a short duration, the MFA actors were instructed to walk from the back of the capture area toward and through the space between the two Kinect cameras. Given the relatively short durations of these walking sequences, they were not long enough in duration to be included in analyses of dynamic structure agreement.

Movement Sequences for the Professor of Theater

The male professor of theater performed *The Rope* and five additional corporeal mime sequences, including a series of four sequences from the Etienne Decroux corporeal mime tradition called the *Actions of Agriculture*. This is a series of four movement sequences that portray features of agricultural work: sowing seeds, pulling a cart, cutting crops with a scythe, and using a pitchfork. The professor of theater's fifth movement sequence was called *Flick of the Seahorse's Tail*, in which he portrayed the dynamics of a seahorse tail through bilateral arm movements.

In terms of testing the motion capture instrumentation, these corporeal mime sequences provided rich and varied samples of human movement. The professor's performance of *The Rope* specifically allowed for an exploration of the properties of expert movement compared to those in training. Like the MFA actors, the professor of theater performed *The Rope* sequence three times during the recording.

Instrumentation

Passive Motion Capture System

A 9-camera MX3/T10 1000 Hz motion analysis system, a passive motion capture system, was used as the gold standard of movement measurement in this study. This is a highly accurate state-of-the-art motion capture system used as a standard for biomechanical research (Windolf, Götzen, & Morlock, 2008). Providing a three-dimensional perspective on movement in the capture area, this allows for highly accurate and reliable recording of kinematics.

Participants were outfitted with specialized light reflectors by experts in the operation of this system. These are designed to be minimally obtrusive, so as not to distort the participant's natural movement. These reflectors are also specially designed to interface with the multiple cameras to produce three-dimensional location data. Before performing the movement sequences, participants stood in the center of the recording space for a baseline snapshot, which this system used as a template for modelling all future movement of this participant. By modelling morphology in terms of marker placement, this method also provided data on body segment lengths for each participant.

Active Motion Capture System

In 2013, Microsoft released a second version of their Kinect camera system, which involves a hardware camera and a linked software development kit (SDK) allowing for data collection and analysis with a personal computer running Windows. Like its predecessor, this version measures human movement in three dimensions over time through a markerless method. That is, a method that does not require the placement of sensors or reflective markers on the participant's body. This system records depth data using infrared sensors. Such data contain three-dimensional information, which can be actively modelled to a human form.

Some approaches to collecting this data use custom programing to extract position data of the built-in skeletal; figure provided by the SDK (e.g., Clark et al., 2012). There also exists third-party software (e.g., Brekelmans, 2016) to capture this raw data directly from the Kinect recording. By these systems, motion capture data of the body segments are directly written and usually only from the perspective of one camera. Though the data can be filtered or cleaned for outliers, the core movement modelling is essentially unalterable for these systems. Video might be recorded incidentally, but once recorded, the movement data are written and cannot be remodeled or resampled after the fact.

The software system utilized in this study is made up of iPi Recorder 3.2.5.47 (iPiSoft LLC, 2016) and the iPi Motion Capture Studio (Basic) 3.4.16.212 with the Biomechanics Add-on (iPiSoft LLC, 2016). This software takes a fundamentally different approach to active motion capture with the Kinect camera (and is compatible with other cameras like the PlayStation Eye). Rather than directly recording skeletal movement data, iPi Recorder first records the depth data over time. In a second step, this video is "tracked" in iPi Motion Capture Studio. It is only at this stage that movement data are modelled.

For the purposes of research on movement dynamics, this step between depth data recording and movement tracking offers advantages for the psychology researcher. One can supervise the movement tracking process and multiple cameras synthesized into a more accurate picture of depth. Regarding the supervision of tracking, one can observe the software estimating movement relative to the observable video. Though this may be rather infrequent, an active motion capture system has the potential of misidentifying or 'losing track' of a body segment through the course of recording, compounding into massive tracking errors. In an active motion capture system that directly records movement data, it is extremely difficult to notice this loss of the segment tracking since there is no visual comparison from which to supervise, and no backup of the depth recording from which to remodel.

Cameras and laptops arrangement. Two Kinect cameras were stationed at the edge of the passive system's pre-existing recording capture area. They were arranged approximately 2.85 m apart and each at approximately a 78° angle. The camera stage right was at a .8 m height over the ground with a slight, 4.26° upward tilt, with the camera stage left at a .9 m height over the ground and a negligible .48° upward tilt.

As the software requires, each camera was linked to dedicated laptop, which were connected by Ethernet cable for reliable simultaneity and data transfer of the two recordings. One laptop-camera pair was dedicated the master controller of the recording process, dictating the start and stop times of the of the slave laptop-camera pair. Cameras were situated on standard video camera tripods set to the sides of a table that had the laptops on it. iPi Recorder software was used to make the depth data recording and facilitate the networking of the machines.

Calibration of cameras. When conducting a multi-camera setup, the spatial relationship between the two cameras needs to be reliably established before the two sets of depth data can be synthesized. This was accomplished by recording a calibration video before any movement sequences can be recorded. An experimenter traversed the capture area with a bright light source in hand, which the iPi Motion Capture Studio software tracks across both cameras. There need not be a strict arrangement of the cameras relative to each other - all successful calibrations are equivalently functional. A second calibration video was recorded at the end of the experimental session in case the camera arrangement of the pre-session calibration was somehow altered (e.g., accidentally bumping a camera), but was ultimately not needed in this study.

Recording procedure. For the active motion capture system, participants are required to begin each movement sequence in a T-Pose (i.e., standing upright with arms held outward, parallel with the ground). Participants were instructed to hold the T-Pose for around 2-3 seconds, after which the participant began the designated movement sequence. The passive motion capture system recording began immediately following the end of the T-Pose stance.

Tracking and refining procedure with iPi Motion Capture Studio. The movement sequences were paired with a calibration file when imported into iPi Motion Capture Studio. A model of each participant was visually fitted to the videos for tracking. Parameters like height, arm length, and leg length, were adjusted to fit the still frame of the participant standing in a T-Pose. Once a model was created for a participant, it was used across all videos of that participant. Videos were then forward tracked under supervision. Whenever a gross error of tracking occurred relative to the original video, the tracking was paused, the human skeletal model manually corrected at the erroneous moment, and forward tracking was resumed. After forward tracking was completed, each video was backward refined. Backward refinement essentially refits the participant's frame-by-frame pose going backwards in time, from the end to the beginning, providing subtle improvements to the initial tracking.

Common Measurement Across Both Systems

Body segments and groupings. Movement of body segments were measured in both systems as Head, Chest, Hips and left and right measurements of Upper Arms, Forearms, Thighs, Shins, and Feet. For all sequences, these body segments were also grouped by summing their respective values for each frame into Upper Body (Head, Chest, Upper Arms, and Forearms) and Lower Body (Hip, Thighs, Shins, Feet). Finally, a Total segments group was created by summing all body segments on their respective values for each frame. Thus, there were 16 values created in total for each movement sequence with 13 body segments and 3 calculated segment groupings.

Frame of reference. The kinematic data from both systems were calculated relative to the global frame of reference. Each body segment was measured relative to the ground and described by kinematics independent of their position relative to other body segments. This can be contrasted with a frame of reference where the kinematics of each body segment is treated relative to their parent joint, for example, the Upper Arm's movement relative to the Chest. Since both systems are calibrated to the global frame of reference, it provided a uniform and identical frame between the two motion capture systems on rotational data.

Sampling rate. I proceeded with 30 hz as the standard sampling rate for all measures. This was the fastest sampling rate permitted for the active motion capture system. The passive motion capture system was sampled at 100 hz, which was transformed into 30 hz by upsampling by a magnitude of 3 to 300 hz and downsampling by a magnitude of 10.

Aligning data. Data were aligned to the correct frame by first gathering an estimate of the corresponding frames between visualizations of the movement data. Second, cross-correlation analyses were performed in R to discover the exact active and passive system frame with maximum correspondence and prepare the data accordingly for agreement analyses.

Data Processing

A major task after the collection of this raw movement data involves processing it into a format from which one can derive meaningful kinematic and kinetic variables. A collaborator and I have written R functions that import movement data and produce segment-wise and whole-body kinematic variables for agreement analyses. Figure 1 depicts the flow of data collection, processing, and analysis.

Magnitude Rotational Velocity

Magnitude rotational velocity captures the movement of each body segment. In this project, it was measured as degrees per second of rotation relative to the global reference system (roughly, relative to the room). It was the primary metric under evaluation in this study as common across the active and passive systems, with the values of the passive system treated as a fixed gold standard. It is also the metric from which dynamic structure calculations are calculated for further evaluation of agreement. Further kinematic variables may be calculated and evaluated along the way, such as other kinematic measures, like acceleration and jerk (the 2nd derivative of velocity). The degree to which the active system measures magnitude velocity accurately directly informs the reliability of future calculations of kinetic measures, such as kinetic energy.

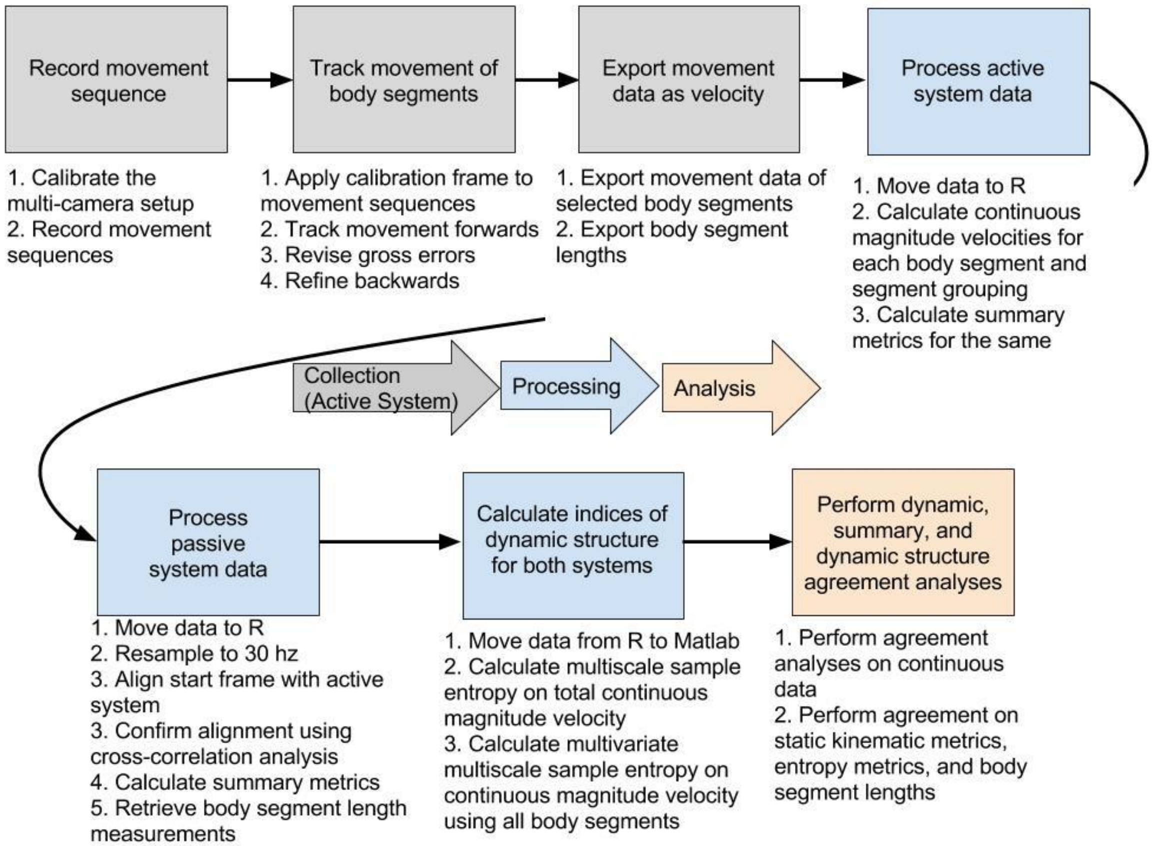

Figure 1. Flow Chart of Movement Data Collection, Processing, and Analysis

Segment Length

Body segment lengths were also measured by the passive system and treated as a gold standard. These were acquired during the pose-fitting phase of the passive system's tracking and are held constant as the passive system tracks sequences for that participant. Likewise, the active system fitted full-body models to the participant before any tracking can be done. This model is held also constant across each of the tracking sequences. Segment lengths were expressed in meters.

Filtering Data

It is common practice to filter biomechanical data to better model true kinematic values, typically with a low-pass Butterworth filter (Winter, 2009, p. 35). Passive system data of the markers were collected at 100 hz, and a residual analysis determined that an optimal filter was a low-pass Butterworth filter at 10 hz.

For the active system, filtering was optimized relative to the processed passive system data as the first step in the data analysis process. The results of this analysis informed the filter order parameters and cut-off frequency for all following agreement analyses. Filtering was performed in R using the *signal* package (2014) and a custom function wrapper used to assess agreement for each movement sequence at many filter combinations.

Complexity

Complexity was operationalized as sample entropy using two closely related algorithms, multiscale sample entropy and multivariate sample entropy. The sample entropy calculation forms the conceptual core of these algorithms (SampEn; Richman & Moorman, 2000). Sample entropy considers a time series sample and tests for patterning in the variability of the data over time. It specifically measures the probability that, over a sequence of m points, that $m + 1$ falls within an acceptable tolerance, r, at other $m + 1$ samples across the time series. Richman and Moorman summarize this as "precisely the conditional probability that two sequences with in a tolerance r for m points remain within r of each other at the next point." (2000, p. H2042). The algorithm counts the number of template matches at m (usually fixed at 2) with the number of template matches $m + 1$, and, to give a standard scaling, takes the negative natural logarithm of this conditional probability. This advances the approximate entropy algorithm (ApEn; Pincus, 1991), which was modelled to capture the mean rate of generation of information in a time series, or Kolmogorov-Sinai (KS) entropy. SampEn specifically is unbiased, but not counting templates as matching themselves, is a better estimate of time series with known complexity, and is more robust to differences in time series length (Richman & Moorman, 2000).

Multiscale. Multiscale sample entropy introduces a multiscale advancement in measurement to this sample entropy algorithm (MSE; Costa, Goldberger, & Peng, 2005). Whereas its predecessors, approximate entropy and sample entropy, consider complexity across a single time scale, Costa, Goldberger & Peng (2005) note that complex processes often happen at different time scales in real-world data. This treatment helps to preserve the entropy metric in accurately characterizing high-information variability as complex, maintaining a guiding intuition about complexity as representing "meaningful structural richness" in dynamic data (Grassberger, 1991, p. 16). The authors of MSE noticed that white noise can often erroneously register as more complex than naturally autocorrelated systems (Costa, Goldberger, & Peng, 2005). By paying attention to larger time scales, MSE can observe long-range dynamic structures typical of living systems. Thus, rather than one scaled value of entropy, this approach generates a series of entropy values for an individual time series, one for each integer increase in time scale (ε).

As an analogy to the changing time scales, consider a digital geographical map. One can zoom in closely to the details of a street and can, step by step, zoom out to a neighborhood, a city, a state or country, and so on. Coarse-graining a time series works this way, but by averaging across bins of time-based data. The multiscale feature of MSE does this very change in scope. An $\varepsilon = 10$ averages bins of every 10 frames of data, $\varepsilon = 20$ across bins of every 20 frames. Thus, when recording at 30 frames per second, an MSE analysis at $\varepsilon = 15$ counts patterns across half-second means.

Multivariate. The multiscale sample entropy measure has been developed further by Ahmed and Mandic to account for complexity in multiple channels of data on the same system (2011). This applies the multiscale approach while considering cross-channel pattern matching *within* and *across* subspaces of a multivariate time series. Where sample entropy requires the fixed parameters of *m*, and *r*, and multiscale modification, of time scale, the multivariate algorithm requires these as well as the specification of time lags among the channels of data (τ). This method generalizes sample entropy to the multivariate case at the specified τ for the specified range of time scales. This is a rigorous and computationally taxing procedure to perform, which grows more taxing as the number of channels increases and the length of the data increase. MATLAB code was publicly shared by the developers of this algorithm and was used in this study to assess both MMSE and MSE (MSE being a 1-channel case of MMSE; Ahmed & Mandic, 2011).

XSEDE high performance computing system. For 13-channel, 5-minute long videos, high performance computing resources were required for most exhaustive test of MMSE. Processing of the multiscale sample entropy algorithms was completed via an allocation of service units on the NSF-funded Extreme Science and Engineering Discovery Environment (XSEDE) which was started at the University of Illinois-Champaign (Towns et al., 2014). The resource that was utilized in this study was Comet, the high-performance computing cluster based in the San Diego Supercomputing Center (SDSC; Moore et al., 2014). For this project, Comet was accessed remotely, and was used to run the MMSE algorithm on fully-prepared time series from both the active and passive systems to examine agreement on these measures.

Data Analysis Strategy

Data analyses focused primarily on the agreement of the active system to the passive system. This is a matter of agreement between a gold standard measure and a trial measure where absolute values are relevant. Additional analyses explored trials for expected features of the multivariate multiscale sample entropy values.

Assessing Agreement

Concordance correlation coefficient (r_c). Statistical analyses on agreement have advanced to the calculation of concordance, which can be decomposed into accuracy and precision (Lin, 1989). A common measure of relatedness, Pearson correlation and its non-parametric equivalents, do not meet the needs of examining the agreement of instrumentation methods. In the case of agreement, it is usually known *a priori* that the systems are measuring that same object. Thus, correlation loses much relevance and the question becomes: to what extent the measures are identical (Lin, 1989, p. 255)? It is important to know how measures agree in terms of scaling (of which correlation is scale-independent); not only whether they are related over time or between trials, but whether they also return similar values of the phenomenon at hand.

The concordance coefficient has been developed to deal with variance between the measures in fixed or random ways, depending on the question at hand. In the case of the current study, variance was treated as fixed, considering the active system and the passive system as composing the population of interest, in comparing a trial instrument to a gold standard without intending to generalize this effect to a larger population (Lin, Hedayat, & Yang, 2002, p. 258-260).

While there are no certain benchmarks for the interpretation of concordance, it is scaled from -1 to 1 and operates similarly to the intra-class correlation coefficient, producing very similar values (Chen & Barnhart, 2008) and might be roughly interpreted with the same rules of thumb of ICC in the social sciences (Cicchetti & Sparrow, 1981). The concordance coefficient is used throughout the current study and is considered the primary measure of degree of agreement. The R package *Agreement* was used to calculate these coefficients (Yu & Lin, 2012).

The precision component of concordance is identical to Pearson correlation, particularly a fixed effects version of the Pearson correlation in the case of assessing concordance to a fixed target (Lin, Hedayat, & Yang, 2002, p. 259). Precision, then, assesses for the structural relationship between measures of the same phenomenon in a relative fashion while the accuracy component assesses for estimation of the measured value in absolute terms.

Limits of agreement and Bland-Altman plots. A way to capture the real-world meaning of r_c is to present the high and low-bound 95% limits of agreement (Barnhart et al., 2016). In the current case, these would be the bounds within which one could expect the active system values to be relative to the gold standard. These values form guiding lines on Bland-Altman plots, which are also generally recommended for visually assessing the agreement of two measures (Bland & Altman, 1986). These plots show the relationship between the average of the two measures and the difference between the two measures, allowing for a depiction of any systematic errors in measurement that might occur and cannot be captured by a single coefficient like r_c (e.g., more extreme errors at the high end of measurement). The R package *BlandAltmanLeh* was used to create these plots and calculate the 95% limits of agreement (Lehnert, 2015).

Three Perspectives on Movement Agreement

In the current study, a passive system designated as a gold standard measure for measuring movement, providing the values for an active system to estimate. Both systems concurrently measured a series of movement sequences. The agreement of active system estimates to the passive system values was assessed through three perspectives: dynamic, summary, and dynamic structure.

Dynamic. One perspective employed in this project was the *dynamic agreement* between the two systems, that is, comparing the continuous, frame-by-frame values of both systems for each segment and for groups of segments (including one of all the segments summed together for each frame) within movement sequences. These agreement indices were then averaged across movement sequences for the main results. These analyses encompass large numbers of observations using core measures of agreement: the concordance coefficient (r_c) precision coefficient (ρ), accuracy (χ_a), and the 95% limits of agreement of values. The 95% lower confidence limit (CL_L) of r_c is also presented with r_c values.

Summary. The second perspective was the *summary agreement*, which involves the analysis of summaries of magnitude velocity across the whole movement sequence. That is, calculating the mean and standard deviation of movement for each segment and segment grouping across the whole sequence. I also assessed the agreement on body segment lengths across participants with the full suite of agreement measures.

Dynamic structure. The third perspective of analysis was on *dynamic structure agreement*. This involves analyses on sets of calculated values that reflect different elements of time series structure: autocorrelation and complexity. Autocorrelation values up to a lag of 90 frames were calculated for body segments and segment groupings for each movement sequence and compared using the suite of agreement measures. Following, agreement between systems on the measures of complexity, multiscale sample entropy and multivariate multiscale sample entropy, was assessed with the same suite of analyses.

CHAPTER 3: RESULTS

Both passive and active motion capture data for all 20 movement sequences were successfully collected with no missing data. I present the agreement between the active and passive systems over time in magnitude rotational velocity in degrees per second. Being a Euclidean-normed scalar the three-dimensional velocity, magnitude velocity gives simplified direct measure of general movement for each body segment over time. That is, it reflects a general "how much movement" recorded from a body segment over time without information about which dimension of rotation (X, Y, or Z) or which direction (positive or negative). In this way, magnitude velocity could be characterized as the omnidirectional rotational speed of a body segment over time. Validating magnitude rotational velocity of each body segment in the whole-body system provides a foundation toward supporting accuracy kinetic energy calculations, the other being accurate measurement of segment lengths. The following analyses include all movement sequences of the experiment by all three participants (N = 20).

Optimal Filtering of the Active System Data

To proceed with the agreement analyses and evaluations of complexity measures, the optimal filtering procedure for the active motion capture data needed to be established. Maximum concordance with the passive motion captures system across movement sequences was determined as the criteria for selecting a specific low-pass Butterworth filter. Optimal filter was operationalized as the filter that, across all body segments over several movement sequences, resulted in maximum frame-by-frame concordance with corresponding passive motion capture segments.

For this analysis, I examined the 1-minute and 5-minute movement sequences of the two MFA actors, 10 in total. For each movement sequence, agreement of the active to the passive system was assessed at 30 digital frequencies (.01 to .30 by .01 increments) for 6 filter orders (1-6). In addition, the agreement of unfiltered data was assessed for comparison. In total, 180 Butterworth filter settings were tested for each of the 13 body segments for 10 movement sequences. I then averaged concordance measures at each Butterworth filter across body segments to get a value of overall performance. Following, averaged concordance across movement sequences was used to derive an optimal Butterworth filter for all subsequent data analyses.

Among tested filters, the optimal low-pass Butterworth filter was a second order filter at a digital filter value of .24. See Figure 2 for a snapshot of five seconds of the male MFA actor's *mock interview* data in the calculated total magnitude velocity. The optimal filter marginally improved upon the concordance coefficient of the unfiltered data: the optimal filter had a concordance coefficient of $r_c = .627$ with a lower-bound 95% confidence limit of $CL_L = .619$ which is larger than the unfiltered data, $r_c = .600$, $CL_U = .613$. The optimal filter made gains in precision to the passive motion capture system over unfiltered data with a $r = .686$ ($CL_L = .671$). The unfiltered data had less precision, $r = .674$ ($CL_U = .656$), the upper-bound of which did not reach the lower-bound of the optimal filter, demonstrating a notable improvement in the optimal filter.

Accuracy decreased with the optimal filter ($r_c = .855$, $CL_U = .861$) when compared to

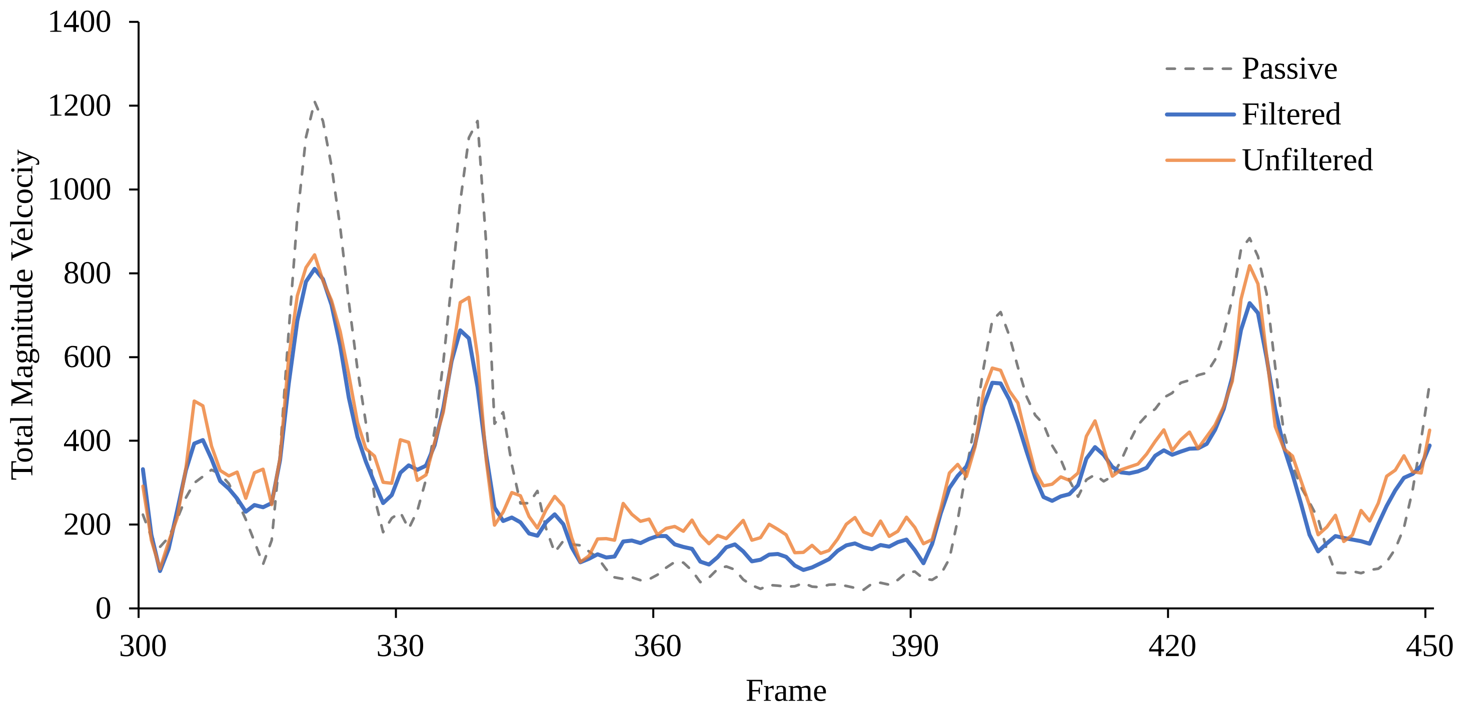

Figure 2. Five Seconds of Filtered and Unfiltered Active System Movement Data in Comparison to the Passive System

the unfiltered data (r_c = .870, CL_L = .863). Given the overall improvement in concordance and the relative importance of precision over accuracy for the purposes of dynamic analyses, I proceeded with the optimal Butterworth-filtered data as the standard for all following analyses.

Dynamic Agreement

Agreement of the active system to the passive system over time was assessed. This focused on the ability of the active system to track the ongoing dynamics of movement. This was performed for each segment and segment grouping for each movement sequence at 30 hz. As an example of the data involved in a single movement sequence, see Figure 3a for the magnitude velocity of all 13 segments through the *Scythe* movement sequence performed by the professor of theater. Figure 3b visualizes the same data as movement.

Across body segments for all movement sequences, the active motion capture system data agreed with the passive motion capture system with an average r_c = .644 (CL_L= .623). This was composed of a precision of r = .694 (CL_L = .670), and an accuracy of χ_a = .883 (CL_L = .868). Body segments had an average rotational magnitude velocity of 57.38 degrees/sec with an average absolute error of 21.83 degrees/sec. The averaged 95% limits of agreement ranged as follows: -59.52 ≤ -.01 ≤ 59.33 degrees/sec. The three sequences with the largest average concordance were two of the movement sequences from the *Actions of Agriculture* performed by the professor of theater (*Scythe* and *Pulling a Cart*), *r* and the male MFA actor's *moving randomly* sequence. The three sequences with the lowest average concordance were the male and female MFA actors' *swaying* sequences and the male MFA actor's *The Rope* sequence. See Appendix B for a table of dynamic agreement results for all sequences sorted by segment-wise average r_c values.

Figure 4 presents a scatterplot with the line of identity and Bland-Altman plot of all recorded movement values. The active system's continuous total values tend to underestimate the passive system's values and there are many observations that fall well outside of the 95% limits of agreement. We can very roughly label an r_c = .644 as "good" for the purposes of social science research based on widely-accepted ICC benchmarks developed by Cicchetti and Sparrow (1981).

There was more agreement between the two systems' frame-by-frame summed totals of all segments, r_c = .676 (CL_L= .661), with a much larger precision r = .835 (CL_L= .819) and a somewhat lower accuracy (χ_a = .798, CL_L= .786). With an average magnitude rotational velocity of 744.66 (SD = 378.20) for the active system, agreement on total values had the following 95% limits of agreement around mean error: -591.63 ≤ -162.98 ≤ 265.68 degrees per second. For an example of this data, see Figure 5 for the first minute of total magnitude velocity values on the female MFA actor's *mock interview*. Table 2 shows the dynamic agreements of segments and segment-groupings averaged across participants and movement sequences. Acceleration agreement was substantially lower across segments, r_c = .356, CL_L = .319, and jerk agreement was even lower, r_c = .216, CL_L = .175.

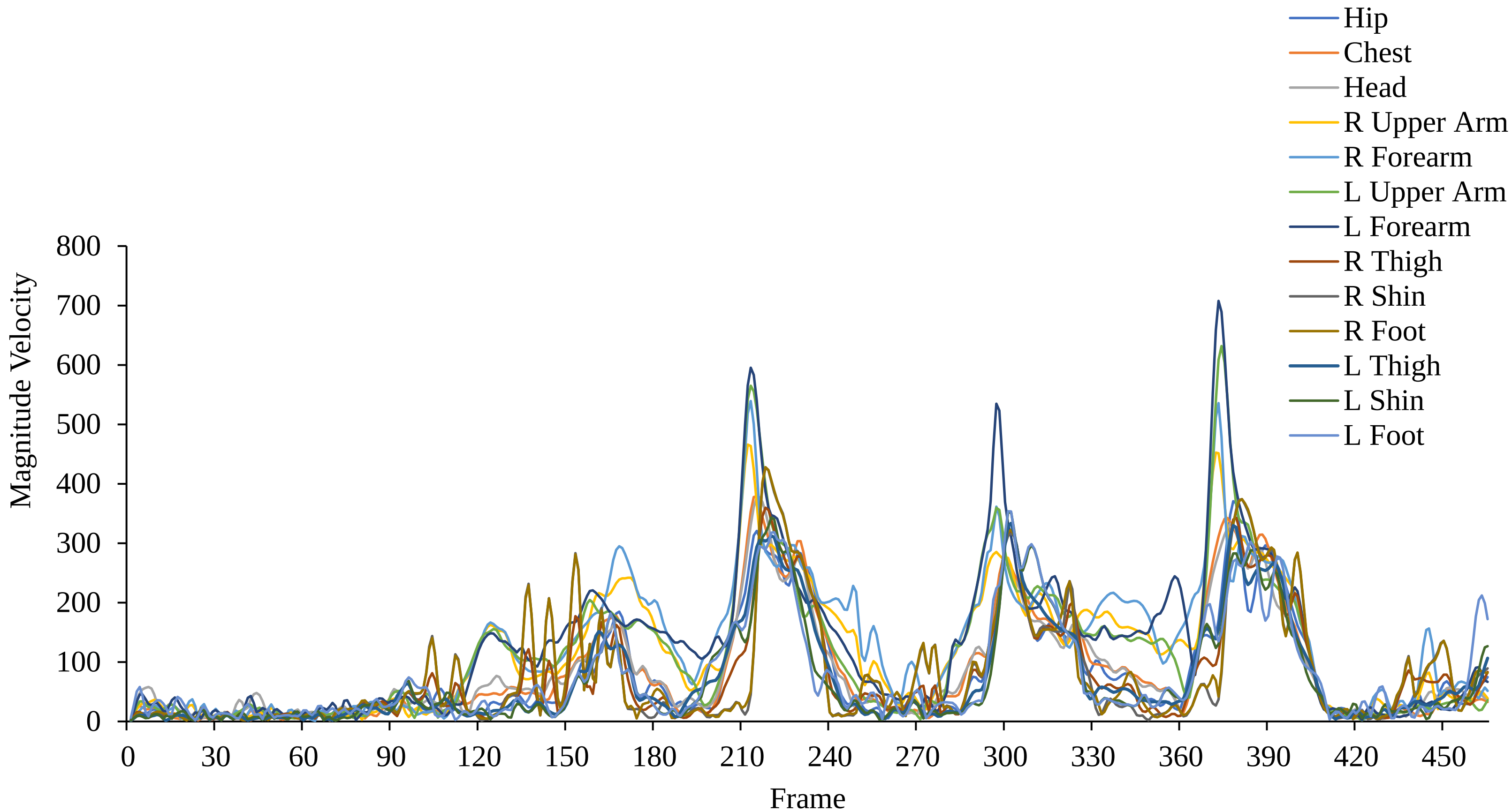

Figure 3a. Movement Data from the Professor of Theater's Performance of the *Scythe* Movement Sequence

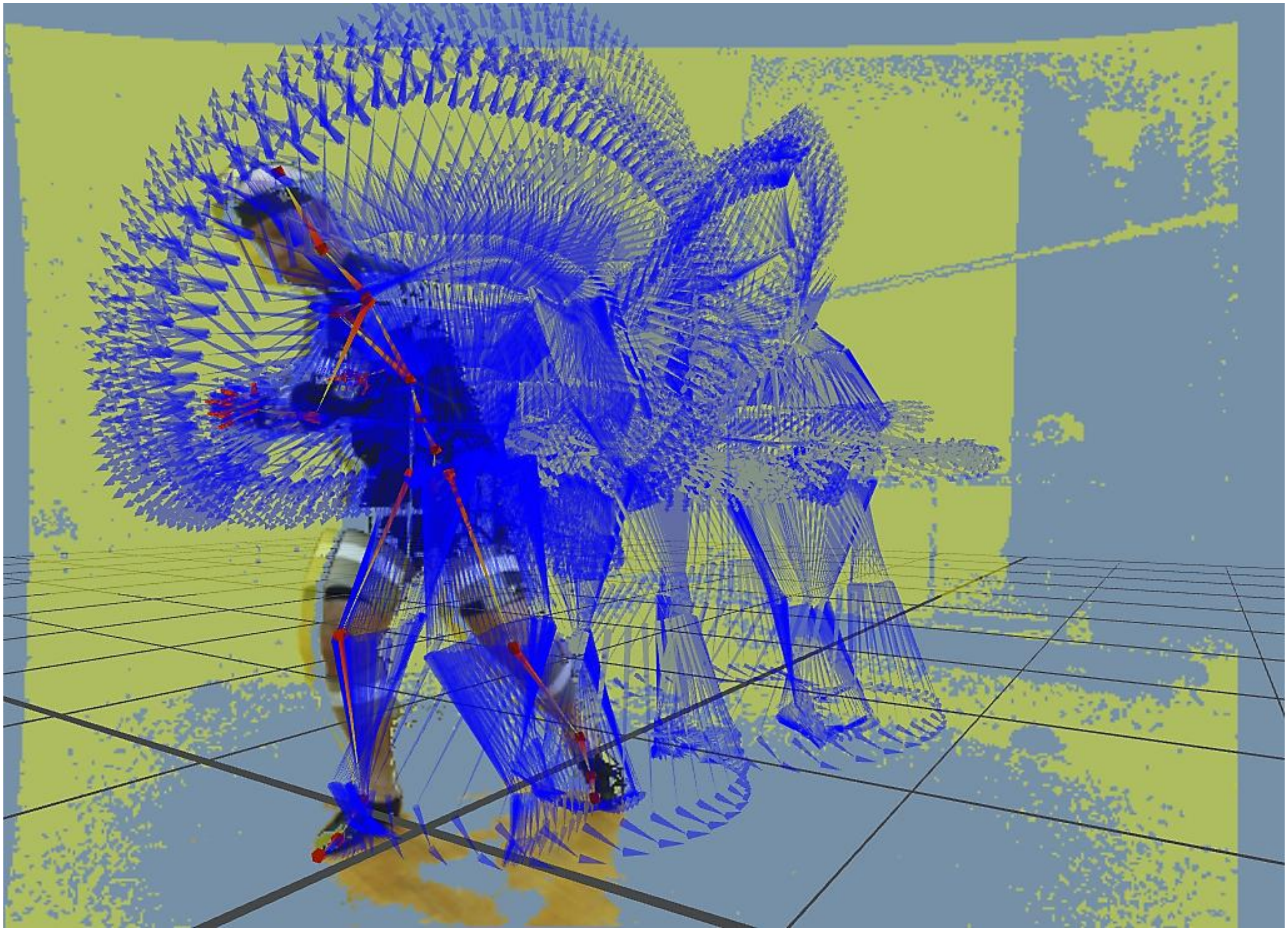

Figure 3b. Visualizing the Professor of Theater's Performance of the *Scythe* Movement Sequence

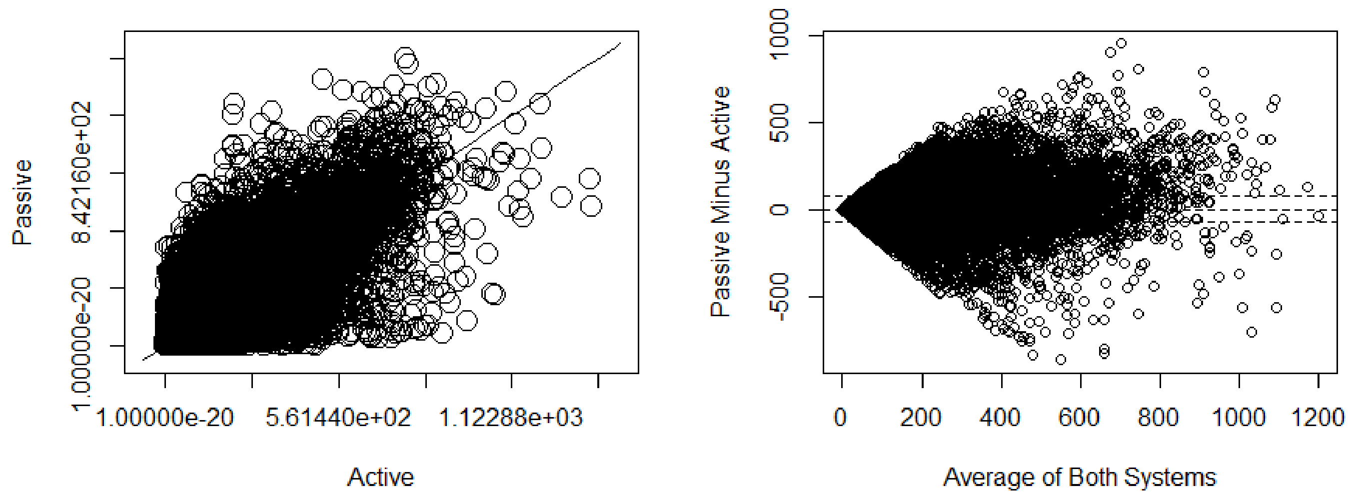

Figure 4. Dynamic Agreement Between the Active and Passive Systems

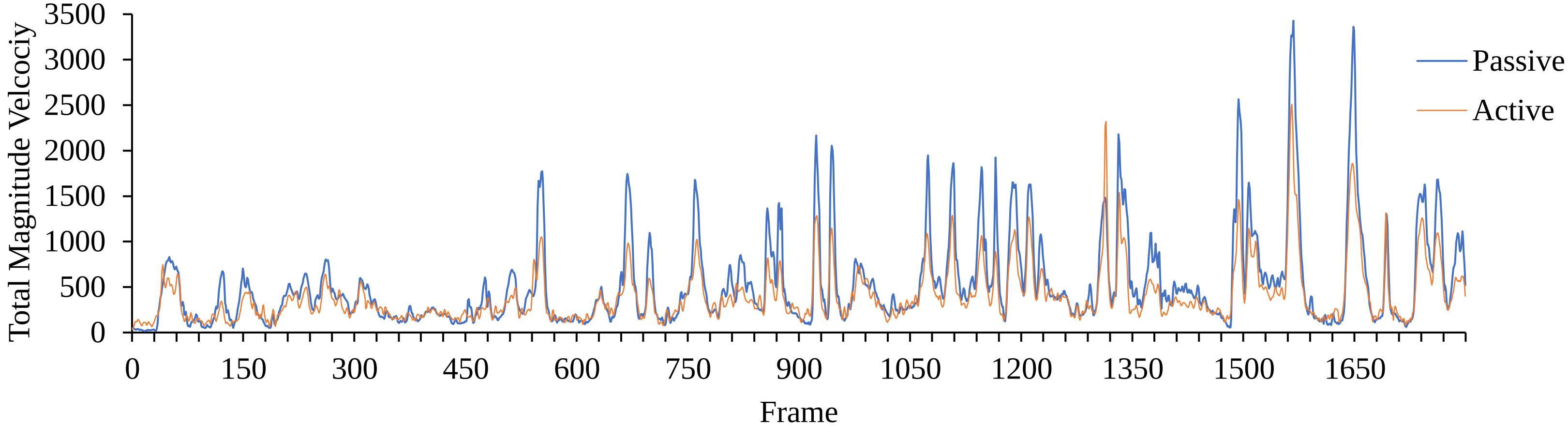

Figure 5. System Comparison of Total Magnitude Velocity in the First Minute of Female MFA Actor's *Mock Interview*

Table 2. Dynamic Agreement Across All Movement Sequences

			r_c Components			95% Limits of Agreement		
Segment or Grouping	r_c	CL_L	ρ	χ_a	Mean (SD)	Lower	Mean Error	Upper
Hip	.40	.37	.48	.75	34.61 (25.42)	-26.29	7.09	40.47
Chest	.62	.60	.68	.86	35.02 (28.41)	-22.25	3.8	29.85
Head	.51	.48	.58	.80	40.27 (31.26)	-35.62	8.25	52.11
Upper Arm (R)	.70	.68	.72	.93	62.54 (48.01)	-57.04	-0.93	55.18
Forearm (R)	.74	.72	.76	.93	85.14 (66.65)	-69.3	3.83	76.96
Upper Arm (L)	.67	.65	.69	.94	62.74 (47.43)	-57.31	0.58	58.47
Forearm (L)	.73	.71	.76	.96	83.2 (63.57)	-71.54	2.64	76.82
Thigh (R)	.74	.72	.77	.93	47.69 (35.14)	-42.47	-1.3	39.88
Shin (R)	.72	.71	.78	.90	59.99 (47.45)	-62.49	-4.66	53.17
Foot (R)	.50	.47	.60	.79	62.17 (49.43)	-115.3	-7.56	100.17
Thigh (L)	.75	.73	.78	.95	48.42 (35.4)	-40.22	-0.54	39.13
Shin (L)	.78	.76	.82	.94	60.27 (49.48)	-57.23	-3.11	51.02
Foot (L)	.51	.49	.60	.80	62.59 (51.48)	-116.68	-9.32	98.04
Averaged Across Segments	*.64*	*.62*	*.69*	*.88*	*57.28 (44.55)*	*-59.52*	*-0.1*	*59.33*
Upper Body	.79	.78	.83	.92	368.92 (237.56)	-176.68	18.16	212.99
Lower Body	.67	.65	.77	.84	375.74 (201.58)	-252.45	-19.4	213.65
Total	.68	.67	.84	.80	744.66 (378.2)	-591.63	-162.98	265.68

Note. Segment Groupings are first summed on magnitude velocity data for each sequence, then agreement is assessed between the two systems. Upper Body is composed of Head, Chest, Upper Arms, and Forearms. Lower Body is composed of Hip, Thighs, Shins, and Feet. (L) and (R) specify left or right side of the body from the participant's perspective.

Summary Agreement

The agreement between systems on the calculated kinematic averages of body segments and segment groupings was then assessed. Average velocity magnitude was calculated for segments and groupings for each system, agreement was assessed for each movement sequence, and agreement values were averaged across movement sequences. The standard deviation of velocity magnitude was also calculated as a summary index of how much velocity values varied across the sequence and subjected to the same analysis.

Across all individual segments, the agreement between the active and passive systems on mean magnitude velocity was extremely high, r_c = .956 (CL_L = .939). The upper body and lower body segment groupings each had extremely high agreement with the passive system (r_{cs} = .985 and .957), while the agreement on mean total velocity was somewhat less, r_c = .878. Overall, the validity of the active system's mean magnitude velocity estimates was high. See Table 3 for a report of agreement between the two systems on segment and grouping-wise mean summary data. A Bland-Altman plot reveals some systematic error in agreement in summary measures, especially at high average velocities (Figure 6).

Agreement on standard deviations of magnitude velocity were extremely high with an average r_c = .921 (average 95% CL_L: .890) across all individual body segments. Standard deviations of magnitude velocity for body segment groups were also in agreement between the two systems, at or above r_c = .913. Agreement on summary acceleration was widely varying across body segments with some still high and others low or even negative, which may reflect a slight alignment artifact between the two streams of data. Jerk (2nd derivative of velocity) agreements were lower, but followed the same pattern, where some segments produced reasonable estimates of this summary value (See Appendices C and D for reports on the summary mean acceleration and jerk agreement values). Acceleration standard deviation estimates were uniformly high as were summary Jerk standard deviation estimates.

Combining perspectives to examine error. With calculations of dynamic agreement for each segment and segment grouping over time and the calculations of mean and SDs of the movement for the passive system, an analysis of patterns in error was possible. I constructed a multiple regression model with summarized mean velocity and velocity SD values from the passive system predicting the dynamic agreement (r_c). Velocity SD was a significant predictor in the model, β = .17, $t(257)$ = 4.68, p < .001, while mean velocity was not, β = -.04, $t(257)$ = -1.25, p = .21. The two predictors were centered to reduce multicollinearity, but were otherwise highly related, $r(258)$ = .91, p < .001. See Figure 7 for a scatterplot of summarized velocity SDs and the dynamic r_c for each unique segment time series, across movement sequences.

Body Segment Length Agreement

Segment lengths measured in meters from the active motion capture system and the passive motion capture system were compared (Figure 8). The active motion capture system models bilateral segments as the same length, while the passive system models all segments individually. I assessed segment length agreement for all three participants (N = 39). The two

Table 3. Summary Agreement Across All Movement Sequences

			r_c Components			95% Limits of Agreement		
Segment or Grouping	r_c	CL_L	ρ	χ_a	Mean (SD)	Lower	Mean Error	Upper
Hip	.93	.89	.97	.96	34.61 (25.42)	-21.88	-7.09	7.7
Chest	.98	.96	.99	.99	35.02 (28.41)	-15.23	-3.8	7.62
Head	.92	.89	.97	.95	40.27 (31.26)	-22.28	-8.25	5.78
Upper Arm (R)	.97	.96	.99	.98	62.54 (48.01)	-24.27	0.93	26.14
Forearm (R)	.97	.96	.99	.98	85.14 (66.65)	-34.55	-3.83	26.9
Upper Arm (L)	.98	.97	.99	.99	62.74 (47.43)	-22.09	-0.58	20.93
Forearm (L)	.99	.98	.99	.99	83.2 (63.57)	-21.56	-2.64	16.29
Thigh (R)	.98	.96	.99	.99	47.69 (35.14)	-14.07	1.3	16.66
Shin (R)	.96	.95	.99	.97	59.99 (47.45)	-22.27	4.66	31.59
Foot (R)	.92	.89	.99	.93	62.17 (49.43)	-35.15	7.56	50.27
Thigh (L)	.98	.97	.99	.99	48.42 (35.4)	-13.81	0.54	14.89
Shin (L)	.98	.97	.99	.98	60.27 (49.48)	-17.51	3.11	23.72
Foot (L)	.90	.88	.99	.91	62.59 (51.48)	-36.57	9.32	55.21
Averages Across Segments	*.96*	*.94*	*.99*	*.97*	*57.28 (44.55)*	*-23.17*	*0.1*	*23.36*
Upper Body	.99	.99	.83	.99	368.92 (237.56)	-112.07	-18.16	75.76
Lower Body	.96	.99	.77	.97	375.74 (201.58)	-140.08	19.4	178.9
Total	.89	.99	.84	.90	744.66 (378.2)	-324.6	162.98	650.6

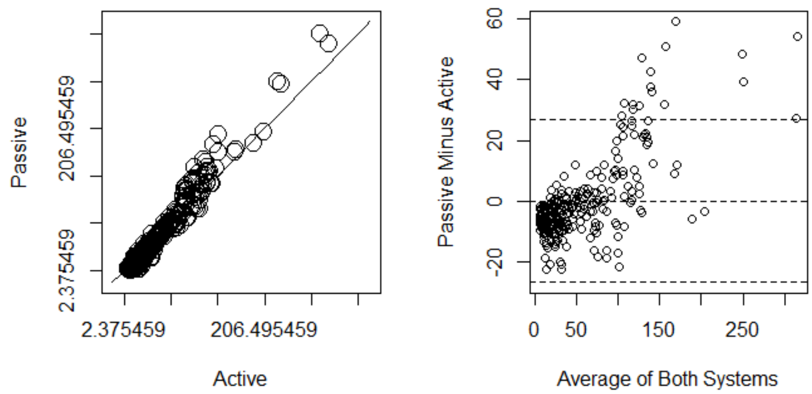

Figure 6. Summary Agreement Between the Active and Passive Systems

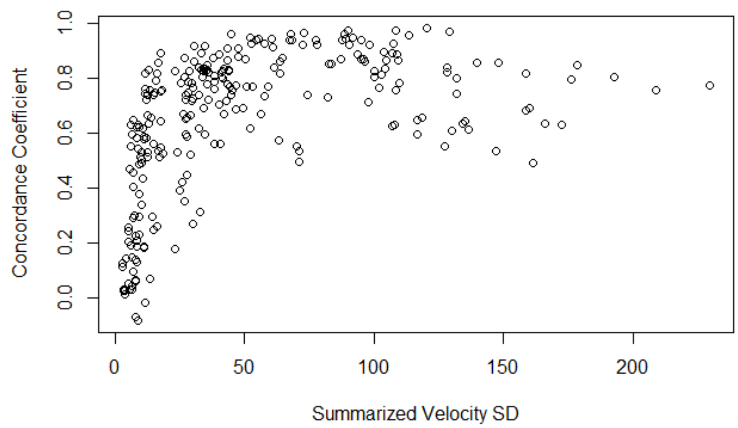

Figure 7. Summary Velocity SD and Concordance Coefficient for All Segments

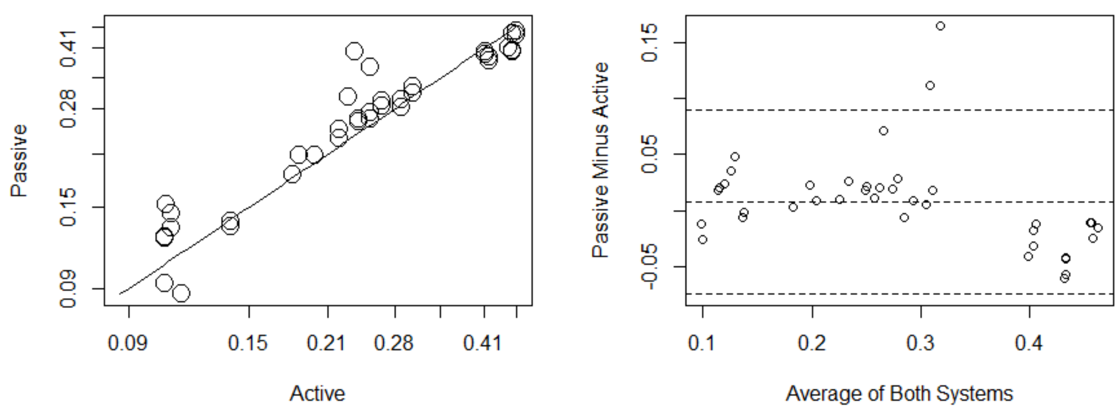

Figure 8. Body Segment Agreement Between the Active and Passive Systems

systems agreed substantially, r_c = .945 (CL_L = .918). For a brief comparison, an assessment of the intraclass correlation between the two systems demonstrated significance and a similar value, ICC3 = .94, $F(38) = 35.51$, $p < .001$. The 95% limits of agreement on body segments was a span of 16.5 cm. See Figure 7 for a scatterplot with identity line and a Bland-Altman plot of the body segment length data. From these plots, one can tell that there is a random arrangement of error with perhaps two outlier measurements where the active system overestimated body segment length.

Dynamic Structure Agreement and Examination

Autocorrelation Agreement

The ability of the active system to model the dynamic structure of the passive system was assessed next. Autocorrelation of each segment up to a lag of 90 (the equivalent of three seconds of data) was calculated for every movement sequence except for the MFA actors' short walking sequences. I assessed agreement for each of these for each movement sequence then averaged the agreement coefficients for each segment and across segments to arrive at total agreement measures. The degree to which the two systems agree on these measures is taken to reflect the ability of the active system to capture a feature of the dynamic structure movement sequence. Correlation values at each lag are the units of comparison.

Averaged across the 13 body segments, there was moderate agreement in autocorrelation profiles, r_c = .828 (CL_L = .804). There was a small mean difference overall, with 95% confidence limits of agreement band within about .17 correlation points in either direction, $-.172 \leq -.001 \leq .170$.

Complexity Agreement

Multivariate and univariate multiscale sample entropy values were calculated for all movement sequences except for the MFA actors' short walking sequences. In general, I sought to examine the agreement of complexity values computed on the data produced by the active motion capture system with those produced by the gold standard. To proceed, I first needed to fix m, τ, and r values for the MSE and MMSE algorithms. Previous research has used $m = 2$, $\tau = 1$, and r = (.15 × SD of z-scored time series) in the description of human gait (Ahmed & Mandic, 2011), so these values were carried forward for these analyses.

Multiscale sample entropy (MSE) agreement. MSE was first assessed in terms of complexity agreement. These were assessed up to $\varepsilon = 10$. There was a relatively low, but still acceptable correspondence between the two systems on multiscale sample entropy values for each epsilon, r_c = .589 (CL_L = .508). With an average sample entropy value of 1.042 (SD = .560) across the two systems, this resulted in a mean difference of .190, with the active motion capture system tending to overestimate the values. The limits of agreement spanned from a lower-limit of -.044 to an upper limit of .424, indicating that any values by the active motion capture system are likely overestimating the univariate sample entropy.

Multivariate multiscale sample entropy (MMSE) agreement. Following, agreement was explored between the two systems on MMSE values up to ε = 20. The systems were in more agreement for this multivariate version of the sample entropy algorithm than the univariate, $r_c = .768$ ($CL_L = .711$). With an average sample entropy value of .108 (SD = .120) across both systems, there was a small mean difference (-.003) and a 95% limits of agreement of $-.066 \leq -.003 \leq .061$.

There were two sequences with very low agreement: the acting professor's *Flick of the Seahorse's Tail*, and the male MFA actor's swaying sequence. These are two sequences where at least a few body segments had very low variability in movement during the sequence. For comparison, when these two removed from the calculations, average concordance increases substantially, $r_c = .867$ ($CL_L = .817$).

Examination of MMSE

Treadmill sequences. To explore the effectiveness of the complexity values in differentiating high and low complexity movement sequences as demonstrated in previous research, I tested for the difference between the complexity values of the two MFA actors on the *free* walking treadmill sequence and the *paced* metronome-regulated treadmill sequence using the values calculated from the active system.

I averaged the corresponding treadmill trials for each actor and conducted a paired t-test comparing the metronome-regulated movement to the normal movement. There were no differences between these values across all time scales, $t(19) = -.92$, $p = .37$, though when looking at the graph, there does seem to be a transition between the two at around $\varepsilon = 5$ (Figure 9). To probe for differences after this transition, when dropping out the first 5 ε, we do see a significant difference, $t(14) = -2.81$, $p = .014$.

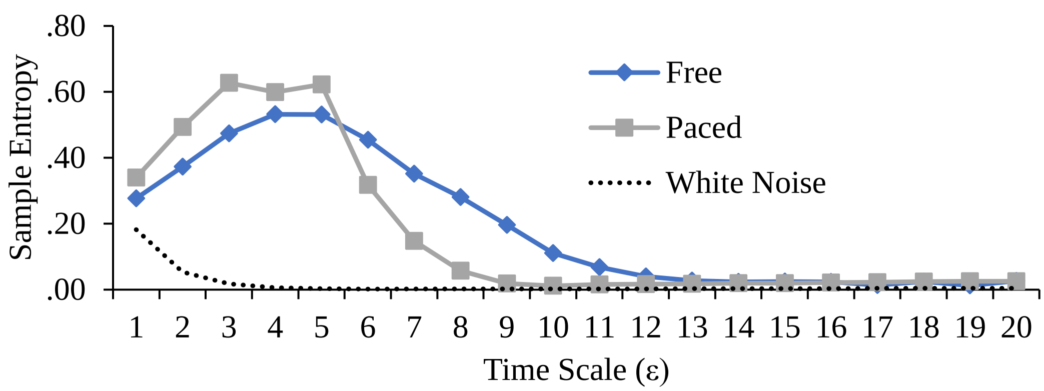

Figure 9. Free Versus Paced Treadmill Walking Complexity

Expertise on *The Rope*. Following, I explored the effect of expertise on movement complexity values. I compared the MMSE values of the expert participant, the professor of theater, to the averaged values of the two MFA actors. There was a large effect of expertise in the complexity of movement across the 20 time scales of sample entropy, $t(19) = 2.89$, $p < .01$, Figure 10. 13-channel white noise complexity is provided for comparison to randomness.

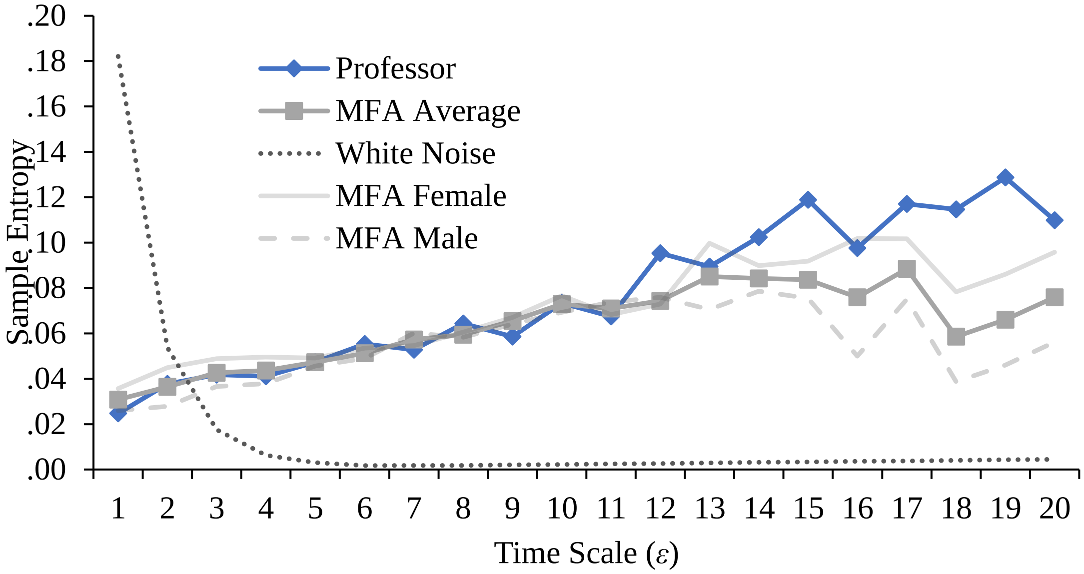

Figure 10. Complexity on *The Rope*

Comparison of *mock interview* to *swaying* and *random* sequences. As a preliminary angle on complexity, I tested for mean differences in MMSE values for the two *mock interview* sequences (both MFA actors) against the averaged multiscale sample entropy across the *random* and *swaying* movement sequences for both MFA actors up to $\varepsilon = 20$. I predicted that the interview sequence would have larger sample entropy values. The opposite was the case. There was a large significant difference between the two averaged sample entropy values, $t(19) = -5.13$, $p < .001$, Figure 11.

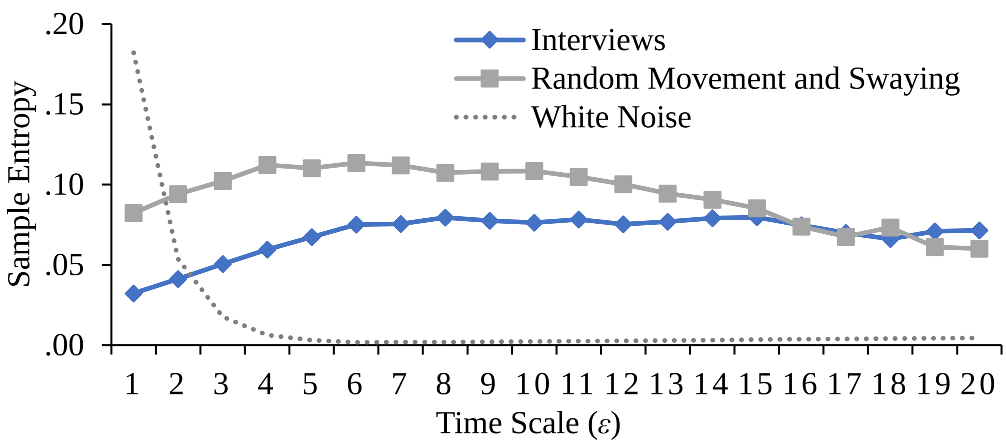

Figure 11. *Mock Interview* Compared to *Random* and *Swaying* Sequences

CHAPTER 4: DISCUSSION

This project attempted to establish the validity of a way to measure movement for the purposes of basic and applied psychology research. This led to the specification of rotational magnitude velocity of body segments and segment groupings as a primary measure of interest given the possibility of this measure in expressing general movement patterns. It also led to the development of a data collection and processing strategy which utilized an active motion capture system. The magnitude rotational velocity provided by this system were compared in kind with gold standard instrumentation in biomechanics. Agreement on body segment values were also explored given its crucial role in future calculations of kinetic energy. Mean and standard deviation summaries of the movement sequence data were calculated and compared for both systems as well and assessed relative to the gold standard. The ability of the active system to capture aspects of dynamic structure was assessed as well, with comparisons between systems on autocorrelation profiles and complexity calculations.

This study revealed that the active system could track dynamic movement - frame by frame- in moderate agreement with a gold standard measure across a variety of movement sequences. In addition, it could characterize movement across a sequence with summary measures (mean and SD of magnitude rotational velocity) in very high agreement with a gold standard measure. A brief comparison of other kinematic measures, acceleration, and jerk, showed that these did not uniformly agree to the same degree. While the active system does not track dynamic movement in such a way that it could somehow replace a gold standard motion capture system, it does seem to reliably estimate the movement dynamics of a sequence, particularly at levels of agreement commonly accepted in social science research. In this vein, the active system's characterizations of dynamic structure, autocorrelation, and complexity, also agreed highly with the passive system. The active system's multivariate multiscale sample entropy was much more accurate than its univariate counterpart, though the validity of the univariate version would likely be satisfactory for large studies. The active system could also accurately model the lengths of body segments of the participants, which when combined with the accurate measurement of rotational velocity and a measurement of an individual's body mass, contains all the values required for the reliable calculation of rotational kinetic energy over time.

Some initial tests of the multivariate complexity measure revealed that it was quite possibly a meaningful measure of structural richness in movement when applied to many channels of magnitude rotational velocity values over time. There was evidence for complexity at time scales greater than 1. At $\varepsilon = 5$, a transition in the complex dynamics of *free* treadmill walking emerged relative to *paced*, while at around $\varepsilon = 11$, divergences between the MFA actors and the professor of theater in movement complexity emerged. Alternatively, multivariate complexity in the *mock interview* sequence was consistently lower than the *random* and *swaying* sequences, in contrast to predictions.

Overall, complexity measures did seem to index the holistic coherence of movement as a kind of gestalt at different time scales, capturing *meaningful structural richness* and perhaps something about the *kinetic melody* of movement. Regarding the *mock interview* sequence, one can reflect on how it was that these were less complex than *swaying* and *random* movement sequences. First, the *swaying* and *random* movements were much more complex than initially expected. It seems that truly rigid swaying or truly random movements are extremely difficult to perform organically and, in fact, these instructions seemed to elicit much coherent whole-body movement. Second, perhaps this complexity structure would come out differently if one were to integrate across biological systems, where including heart rate or electroencephalogram (EEG) dynamics might have disproportionately contributed to the *mock interview* complexity. That said, there was a convergence in the complexity of these time series around $\varepsilon = 16$, signaling that, despite being less information-rich on the small scale, the actors' movements during the *mock interview* held a similar complexity structure at large time scales.

Limitations

Some limitations of the study presented here should be addressed in guidance of further research. First, the movement recording and data processing setup presented in this study does not record hand movement. The Xbox Kinect system is highly developed to record hand movement, even to the specificity of the angles of joints within fingers, so it would in principle be possible to obtain hand movement if they are of interest for a given research question. However, using other proprietary systems or directly importing data from the Kinect SDK runs the major disadvantage (deemed too great in the current project) of recording movement blindly. One captures movement once and is unable to refine or correct the model relative to actual video. In any event, it is not known how accurate the Kinect version 2 is in recording fine motor movement of the hand, but it does seem capable of capturing reaching behavior at a larger scale.

Second, this study only utilized two Kinect version 2 cameras in the capturing of movement. At least with a professional edition of iPi Motion Capture Studio, it is possible to record and synthesize the depth data of up to four Kinect version 2 cameras at once. This would unfortunately require four different computers linked via a Local Area Network due to the design of the Kinect drivers, but it seems that such a setup would only improve the accuracy and reliability of the Kinect recordings. PlayStation Eye cameras can be used as well, and permit an increase to 6 or more concurrent recordings for iPiSoft software. The results of the current study suggest that such setups should be similar or better at recording movement as rotational velocity.

Third, the current study did not directly address test-retest reliability of the active motion capture system relative to the gold standard system. Such assessment would lend even more credence to system's ability to measure movement. One caveat to this limitation is that with the process presented in this work, the actual movement tracking can be visually supervised relative to the raw video. That is, one can watch the system as it tracks movement from the video and monitor for gross errors. In the current study, it is an educated guess that correcting for gross errors led to qualitatively different agreement results (e.g., correcting an arm segment tracking from being completely unhinged from the actual video). Anecdotally, when these massive losses of tracking occur, the motion capture systems rarely recover or self-correct and errors only compound over time.

Directions for Dynamic Movement Processing and Analysis

There may be ways to improve the data processing and analysis of movement. I review a few areas that emerge as potential directions for the development of the data processing and analysis of movement data. One over-arching direction in this area would be to develop ways to ease the implementation of movement data collection in clinical and experimental psychology research. The development of publicly-available R functions, which would likely be generalized versions of the functions developed for this project, might aid investigators in crossing the gap to implementation.

Removing Low-Performing Segments and Refining Segment Calculations

By refining the whole-body model to remove low-performing segments, overall model reliability would increase. Of course, this should be weighed against the downside of losing a segment in the model. For example, the feet were low-performing and may not be too central to the success of whole-body modelling of movement, while the head also be relatively low-performing, but perhaps more theoretically important for expressive movement (see Ramseyer & Tschacher, 2014). Likewise, the calculations of some segments might improve if the velocity magnitude calculations are restrained to the most relevant degrees of freedom at the level of segments. While the head may theoretically rotate in three degrees of freedom, segments like the shin (rotating at the knee) do not - especially when considering the properties of everyday expressive movement. Calculating magnitude velocity in this way may reduce the overall noise in the dynamic models and improve agreement further. Similarly, somehow removing segments below a certain threshold of velocity variability may dramatically improve reliability of measurement.

Dimension Reduction with Segment Groupings

With a set of data, even perhaps the data presented in this study, one could perform an exploratory factor analysis to determine whether there are prevailing subgroups of body segments across participants and simplify the description of whole body movement to these groups. This approach runs the risk of over-simplifying what might be a wide diversity of movement patterns across participants, but may improve the parsimony of the data. Reductions along these lines would also aid in making computationally-intensive data processing, like the multiscale multivariate sample entropy calculations, possible on long duration recordings without the need to enlist supercomputing. Without knowing more about how expressive movement dynamics operate, preserving high-dimensional models of movement may help to capture complexity and coherence in movement more accurately.

Including movement data of the center of mass, which is automatically calculated with the Biomechanics add-on for iPi Motion Capture Studio, may be an avenue for summarizing major features of movement succinctly. On the other hand, there are a few additional segments available that one may add as channels in data output (e.g., different sections of the spine).

Relative Frame of Reference

Using a relative frame of reference, that is, defining a segment's movement relative to the higher-order, parent segment rather than to the ground, might reduce redundant body segment intercorrelation, permitting a more exact description of movement dynamics. This may reduce noise in models attempting to estimate how the whole body moves as a coherent whole.

Kinetic and Potential Energy

Some directions in the measurement of movement dynamics would be to move forward with kinetic energy calculations (Robinson et al., 2013, p. 132). Further models could incorporate translational movement (instead of only rotational) into the overall modelling of movement may also improve accuracy, especially in the description of whole-body kinetic energy. With rotational velocity as the main ingredient of *rotational* kinetic energy calculations, creating an even more accurate model of *total* kinetic energy in concert with the most advanced practices of biomechanics methodology would only advance the purpose of developing a whole-body model of energy dynamics for psychology research. Measuring and incorporating potential energy dynamics is eminently possible, as well, allowing for the calculation of total energy dynamics. This would offer yet another layer of data for operationalizing questions regarding personality, affect, and character.

Optimizing MSE and MMSE Parameters *m, τ,* and *r* for Expressive Movement

In this project, standard values of m, τ, and r from the developers of the MMSE algorithm (Ahmed & Mandic, 2011) were used for the MSE and MMSE analyses. There may be larger patterns (*m*) that are relevant to the complexity of movement. Moreover, there may also be important intercorrelations that occur over a larger time span, τ. Further research should establish optimal parameters for the case of expressive movement so as to capture the dynamic structure of a sequence more fully.

Directions for Dynamic Movement Research in Empirical Psychology

Affect Regulation

An impetus for the development of this instrumentation procedure came from clinical psychology and phenomenology, where it was noticed how movement dynamics might be relevant to dimensions of affect regulation, especially those occurring implicitly, reflecting an embeddedness in an individual's background affective experience (Ratcliffe, 2008). Capacities for self-regulation are thought to be a relevant transdiagnostic feature for understanding psychopathology and a component of mentalization. Optimal regulation of affect under social stress can be theoretically equated with the presence of a secure attachment style (Cassidy, 1994). Rooted in early interactions with primary caregivers, highly relational styles affect regulation seem to transform, as one moves into adulthood, into capacities for mentalization and for experiencing states of mentalized affectivity (Fonagy et al., 2004). However, the role of whole-body movement in the maintenance of these styles may somehow remain.

One could tailor phenomenologically front-loaded (Gallagher, 2003), behavioral-experiential paradigms to examine interactions of experience and dynamic movement in affect regulation. Assessing movement in theoretically-informed situations (e.g., under social stress) may also more generally allow for the examination psychodynamic perspectives on character and anxiety (Shapiro, 2002). While relevant psychodynamic phenomena might more traditionally be conceptualized as discrete unconscious events or schemas, are increasingly conceptualized in ways that fit the model of dynamic movement – for example, as the neuropsychological processes (Solms, 2013) or interpersonal dynamics (Eagle, 2011).

As multiscale sample entropy appears to be a promising metric in the study of movement, it may prove useful in examining implicit affect regulation. Measuring movement variability may free from some methodological limitations, but it also underlines the importance of other features of the measurement situation. In attempting to measure dynamic affect regulation across participants, one must reliably define the situation. In addition, one must select a situation that reliably engages an individual's capacities for regulation and allows for whole-body movement.

In the clinical neurobiology literature, there exists a well-studied situation for the induction of interpersonal stress that satisfies these important features of a whole-body measurement situation: the Trier Social Stress Test (TSST; Kirschbaum, Pirke, & Hellhammer, 1993). The TSST tasks participants to a well-defined interview task that reliably induces stress. This paradigm is an example of a good balance of experimental control with degrees of freedom in expressive movement.

Interactions of Movement with Other Systems

With reliable measurement of movement dynamics, one could investigate the integration of multiple systems in a person over time. Movement data could be coupled with EEG data to explore synchrony or even causal chains between brain activity and motor behavior over time using existing statistical modelling in these areas, like dynamic causal modelling (Friston, Harrison, & Penny, 2003). Neurophenomenology and phenomenological approaches to cognition have already empirically examined questions about temporal self-constitution to examine the process of prereflective awareness (Thompson, 2007; Varela, Thompson, Rosch, 1991). To the extent that dynamic structures of movement are involved in the articulation of awareness, integration with EEG methodology may be a way to deeply explore individual differences in implicit affect regulation.

Similarly, the convergence of movement with heart rate or skin conductance could be investigated to explore individual differences in sympathetic and parasympathetic nervous system function with movement, for example, with and without stress. These approaches might specify overregulation and underregulation dynamics of self-regulation (Cassidy, 1994) especially across bodily systems (Siegel, 2012).

There may be a possibility of exploring movement dynamics in relation to spoken language at the levels of prosody or semantics. Regarding the study of dynamics of semantic quantitative linguistics (e.g., sentiment analysis) might be particularly productive (Tausczik & Pennebaker, 2010). Some measures exist for exploring the coherence of a text (e.g., Latent Semantic Analysis; Günther, Dudschig, & Kaup, 2015), and the degree to which linguistic coherence and movement complexity correspond would be an interesting question for work on the embodiment of language and cognition (Lakoff & Johnson, 1999). Generally, these forays into cross-system interactions may allow for the empirical investigation of personal and characterological integration.

Psychotherapy Process and Outcome

Applied opportunities also emerge with disciplines where concrete human bodily movement is relevant to clinical phenomena. An applied clinical direction would be the exploration of psychotherapy process, in terms of following interpersonal movement dynamics in whole-body interactive models over time in both the patient and the therapist. While it may contribute in a small way to current methodology in synchrony, where simpler video-based methods may be sufficient (Ramseyer & Tschacher, 2011), it is possible that this may provide a level of richness required to adequately assess complex relational dynamics, like transference/counter-transference relations, which are often theorized to develop in large part via enactments in the therapy room (Eagle, 2011). Likewise, the enhanced tracking benefitted by a motion capture approach might expand interactional synchrony models (Delaherche et al., 2012; Paxton & Dale, 2013), particularly by elaborating the role of animate *intra*personal organization in the presence of the other.

With a stronger basic knowledge of the interaction of movement and affect regulation, there may be movement-based assessments for the indexing and tracking of clinical phenomena. Developmental of assessment protocols with different targeted movement sequences, analogous to a series of Rorschach cards, might be able to assess features of character and affect regulation – generally, the dynamic congruency of emotion and movement. Large samples of standardized movement sequences from individuals with known characterological features might be described with machine-learning algorithms to describe relevant movement from the ground up.

Movement Training

A different track of interdisciplinary work could explore expressive movement in the context of corporeal mime, dance, or theater (Decroux, 1985; Leabhart, 1989; Sheets-Johnstone, 1966). This would be a useful collaboration toward promoting the description of movement sequences for training purposes. At the same time, such a collaboration may also help to hone a psychological theory of movement dynamics for the purposes of experimental psychology or applied clinical settings. While theoretical approaches around these topics would be inherently useful, an advantage of valid movement data collection is that is can both ground operationalization of theory and inspire further work with empirical insights. Precedent exists for the study of complexity dynamics and experience of expert artists which has mutually informed the contributing disciplines. For example, Williamon, Aufegger, Wasley, Looney and Mandic (2013) demonstrated complexity loss in heart rate under conditions of stress in an expert concert pianist.

Clinical Neuropsychology

Though largely unexplored in this project, it does seem that studying the movement of individuals struggling with neurological disorders (including attention-deficit hyperactivity disorders) may help to characterize motor control at different time scales, which may be relevant to different neuropsychologically-relevant subsystems of movement and affect (Kaplan-Solms & Solms, 2002; Panksepp, 2014). It is possible that this instrumentation could be paired with any number of movement sequences that highlight features of motor control. But also, this method may allow for the assessment of subtle differences in affect regulation and character in disorders of the central nervous system, like Central Sensitization Syndromes, where widespread pain-sensitivity seems to have psychosomatic consequences (Yunus, 2007). Likewise, it seems flexible and reliable enough, having worked across many forms of movement in this study, to adapt to such situations well. Similarly, it seems like this system would be well suited to inform the diagnosis and treatment of individuals with sensorimotor coordination problems (Miller, Anzalone, Lane, Cermak & Osten, 2007).

Conclusion

The opportunity to study whole-body movement dynamics opens a methodological window into core problems at the nexus of phenomenology and psychology: self-regulation, the process of human embodiment, affect consciousness, pre-reflective and reflective experience. It allows for specifying behavior as kinetic melodies (Luria, 1973; Merleau-Ponty, 1942/1983) and considering the ways that neurological and other bodily systems interact – or form a coherent whole – over time. Sheets-Johnstone describes what is at stake when we overlook whole-body dynamics when considering human experience:

> To omit attention to whole-body dynamics is to reduce the dynamics of emotion— and more particularly, the dynamic form of an emotion as it unfolds — to a single expressive moment or to isolated internal bodily happenings. It is to de-temporalize what is by nature temporal or processual. Correlatively, it is to skew the evolutionary significance of emotion, which is basically not to communicate, but to motivate action. (1999, p. 273).

Research in this direction has lacked a reliable and accessible methodological tool. With this project, I introduced a procedure that can be used to capture and describe the dynamic structure of raw movement. I also described some directions that may prove useful for the development of methods and theory for research on the animate body. This methodology indexes behavior as a temporal process rather than a discrete act and, in that way, may be a key toward empirically examining structural richness in movement.

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APPENDICES

Appendix A. Rotational Kinetic Energy

In order to provide an estimate of kinetic energy output for each limb at each time point, I employ the following function in the three planes of rotation for each body segment (Robertson, et al., 2014, p. 137):

$$KE_{rotational} = \frac{1}{2} I \omega^2$$

In this equation, ω stands for the segment's rotational velocity at a given plane of rotation and I stands for the segment's moment of inertia in that same plane. I can calculate the moment of inertia (I_{cg}) in a given plane as a proportion of the segment mass (m) to the square of the segment's radius of gyration (k_{cg}; Robertson, et al., 2014, p. 72):

$$I_{cg} = mk_{cg}^2$$

Radii of gyration serve as indirect estimates for the location of the moment of inertia according to the average adult human body. I employ De Leva's adjustments to the Zatsiorsky- Seluyanov measurements in our model of kinetic energy for each plane, which provide indices for determining the location radii of gyration separately for male and female adults (1996). These indices (K_{cg}) are multiplied by the segment length (L) in order to arrive at the specific radius of gyration location for each participant in each rotational plane (Robinson et al., 2014 p. 71):

$$k_{cg} = K_{cg} L$$

Following, I calculate the Euler vector norms for the kinetic energy value at each frame for each segment across the three rotational planes. Summing the kinetic energy across segments at each frame provides the whole-body kinetic energy for that frame.

Segment Mass

There are a number of human models proposed to accomplish the estimation of each segment of the body by providing proportions of each segment mass relative to the whole body mass (Robinson et al., 2014, p. 65). I employ De Leva's parameters for this metric (1996). Similar to the coefficients for the radii of gyration, different proportions are applied by gender. For example, the forearm is modelled as being 1.38% of the total body mass for females and 1.62% of the total body mass for males (De Leva, 1996, p. 1228). Thus, each participant's total body mass and gender are required for the calculation of each segment's kinetic energy across frames. These segment energies are also summed for each frame, providing an estimate of whole-body kinetic energy output at the original time resolution.

Appendix B. Dynamic Agreement by Movement Sequence and Sorted by r_c

Participant	Movement Sequence	r_c	CL_L	r_c Components ρ	χ_a
Professor of Theater	Scythe (AOA)	.93	.92	.93	.99
Professor of Theater	Pulling a cart (AOA)	.84	.83	.87	.96
Male MFA Actor	Random	.83	.82	.84	.98
Professor of Theater	Sowing seeds (AOA)	.79	.78	.83	.95
Professor of Theater	Pitchfork (AOA)	.77	.75	.79	.97
Female MFA Actor	Random	.77	.76	.81	.94
Female MFA Actor	Mock stress interview	.74	.73	.75	.98
Male MFA Actor	Mock stress interview	.70	.70	.76	.92
Female MFA Actor	Free treadmill	.67	.65	.71	.92
Female MFA Actor	Paced treadmill	.66	.65	.72	.91
Male MFA Actor	Free treadmill	.64	.63	.72	.85
Professor of Theater	*The Rope*	.62	.60	.69	.86
Male MFA Actor	Paced treadmill	.62	.61	.70	.80
Female MFA Actor	Ground walking	.57	.50	.61	.92
Professor of Theater	*Flick of the Seahorse's Tail*	.56	.53	.68	.82
Male MFA Actor	Ground walking	.55	.46	.60	.88
Female MFA Actor	*The Rope*	.54	.52	.61	.84
Female MFA Actor	Swaying	.47	.45	.49	.93
Male MFA Actor	*The Rope*	.33	.32	.42	.61
Male MFA Actor	Swaying	.29	.27	.36	.63

Note. Results are averaged across all segments. AOA indicates a movement sequence belonging to the corporeal mime *Actions of Agriculture* series.

Appendix C. Summary Agreement on Acceleration Means

			r_c Components	
Segment or Grouping	r_c	CL_L	ρ	χ_a
Hip	.66	.57	.88	.76
Chest	.05	-.26	.07	.82
Head	-.59	-.73	-.71	.83
Upper Arm (R)	.79	.65	.83	.96
Forearm (R)	.87	.78	.89	.97
Upper Arm (L)	-.74	-.83	-.85	.87
Forearm (L)	-.36	-.46	-.69	.52
Thigh (R)	-.29	-.40	-.69	.42
Shin (R)	.99	.98	.99	.99
Foot (R)	.90	.89	.99	.90
Thigh (L)	-.22	-.29	-.67	.33
Shin (L)	.36	.09	.43	.84
Foot (L)	.51	.35	.76	.67
Averages Across Segments	.23	.10	.17	.76
Upper Body	.16	-.02	.30	.52
Lower Body	.82	.77	.97	.84
Total	.72	.64	.92	.78

Appendix D. Summary Agreement on Jerk Means

			r_c Components	
Segment or Grouping	r_c	CL_L	ρ	χ_a
Hip	.62	.54	.90	.68
Chest	-.33	-.52	-.48	.70
Head	-.15	-.31	-.32	.48
Upper Arm (R)	.82	.74	.89	.92
Forearm (R)	.44	.37	.90	.49
Upper Arm (L)	.35	.27	.77	.46
Forearm (L)	.76	.72	.98	.77
Thigh (R)	.56	.52	.98	.58
Shin (R)	-.45	-.56	-.78	.57
Foot (R)	.44	.31	.79	.55
Thigh (L)	.50	.39	.76	.66
Shin (L)	-.02	-.28	-.02	.69
Foot (L)	.06	-.11	.13	.44
Averages Across Segments	.28	.16	.42	.61
Upper Body	.47	.38	.83	.57
Lower Body	.48	.42	.92	.52
Total	.58	.50	.90	.64

VITA

Michael T. Finn was born in Cincinnati, OH. He grew up there and in Grand Rapids, MI. He obtained a B.A. with Highest Honors in Psychology and Spanish Language and Literature from the University of Michigan before enrolling at the University of Tennessee, Knoxville in the Clinical Psychology PhD program. There, he has worked as part of the Laboratory for the Empirical Study of Psychodynamic Processes and Psychotherapy and has done psychotherapy and psychological assessment. During his studies at the University of Tennessee, Knoxville, he took leave for a year to pursue a research fellowship in Heidelberg Germany where he studied phenomenology and psychopathology. He has published articles on embodiment in psychopathology, psychological research methods, time series analysis, and the cognitive/affective features of hypnosis experience.