QUALITATIVE MOVEMENT ANALYSIS FOR HUMAN-COMPUTER INTERACTION

THESIS

Submitted in Partial Fulfillment of

the Requirements for

the Degree of

MASTER OF SCIENCE (INTEGRATED DIGITAL MEDIA)

at the

NEW YORK UNIVERSITY

TANDON SCHOOL OF ENGINEERING

by

Caitlin Sikora

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QUALITATIVE MOVEMENT ANALYSIS FOR HUMAN-COMPUTER INTERACTION

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VITA

Caitlin Sikora graduated cum laude and Phi Beta Kappa from University of California, Irvine with a BA in Dance and a BS in Physics with Campus-wide Honors and Honors in Physics. In her time at UCI, two of her choreographic works were showcased in Dance Department performances, and she was honored with the award for Outstanding Undergraduate Research in Physics for her investigation of leptogenesis under the mentorship of Dr. Mu-Chun Chen. Sikora also designed and taught a seminar to UCI undergraduates on the Physics of Dance in the pilot year of the UTeach Program.

Sikora performed professionally with Winifred Harris's Between Lines Dance Company, Indah Walsh Dance Company, and the Hannah Kahn Dance Company. Her choreography has been performed at the Warwick Summer Arts Festival, Flux Factory, and Boulder International Fringe Festival. Sikora has enjoyed positions on the faculty at Colorado Ballet and International Ballet School.

In 2015, Sikora completed her MFA in Dance at NYU's Tisch School of the Arts, where she received two interdepartmental grants to collaborate with students in NYU ITP on movement and technology projects. In 2015, she was awarded a residency hosted by Danspace Project, where she investigated sensory perception and decision-making processes in choreography and improvisation. Subsequently, she researched movement responses to sensory inputs in a project called ProprioLoop at MotionBank's Choreographic Coding Lab, subsequently featured at MIT's Hacking Arts Festival.

In her studies at NYU's Tandon School of Engineering, she focuses on analyzing and generating motion capture data, creating movement-based interfaces between humans and computers, and developing wearable and assistive technologies.

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ABSTRACT

Qualitative Movement Analysis for Human-Computer Interaction

by

Caitlin Sikora

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The sensing, interpreting, and designing of movement for interacting with computing systems could allow machines greater capacity to interpret the actions of users to decipher user intention, as well as to communicate personalized, nuanced messages to meet individualized user needs, emulating conversation between humans. Harnessing the power of human movement as a medium for communication in the context of technology would have applications in the design of more sensitive assistive technologies, more perceptive smart homes, and more socially capable robots and conversational virtual characters. In order to realize this vision, we must improve our understanding of how humans imbue and extract meaning in and from body movement so that we can program computers to do the same.

Traditional linguistic and cognitive science approaches to interpreting meaning from movement tend to consider shapes of specific, culturally defined gestures, timing of gestures

with speech, and spatial referencing of deictic gestures (pointing). Interfaces between humans and computers echo this line of reasoning with one-to-one associations of mechanically specific movements and deictic gestures dominating the design of movement-based interactions. Execution of such gestures, even when they are intuitive, must be performed quite intentionally, but we can see from the literature in the cognitive sciences that non-verbal communication and interpretation are performed at non-conscious levels of processing. In order to capture emotional state and intention communicated non-consciously through movement, I suggest we look to methodology from the field of dance.

The studies of choreography and Laban Movement Analysis in the dance discipline offer systems for interpreting meaning from a person's physical movements based on quality and context that can be generalized to establish a lexicon of detectable, expressive qualities in human movement that should inform the design of gestural interfaces, both on and off the screen. In this paper, we conduct a series of pilot studies to assess the relevance of the Laban Effort system for classifying movement quality to the design of gestural interfaces. By conducting surveys in which human, non-expert participants label the movements of other humans with Laban Efforts and emotional interpretations, we determine that humans can recognize at least a subset of the Laban Efforts with a reasonable degree of reliability. Moreover, humans are likely to non-consciously perform these movement qualities when engaged in emotionally charged conversation and expression. We complete this research by drawing connections between several of the Laban Efforts and consistently interpreted and experienced emotional intentions. Future work will strengthen associations between the qualities and their emotional meanings to provide a framework for their use in the design of gestural interfaces.

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INTRODUCTION

In Western society, as the presence of technology in everyday lives has increased, we observe a need for more intuitive human-computer interfaces. Between desktop and laptop computers, smart phones, and interactive systems in transportation, retail, and museums, humans today spend almost as much time interacting with technology as with other humans. Although the capabilities and availability of computing systems have grown significantly in the past few decades, we have not yet observed a paradigmatic shift in how we interact with them. Rather, we have seen incremental advancements of the same ideas that prevailed in the 1980's: we point to and click on graphical objects in menus, push buttons, and type strings of text to interact with computers. Despite the addition of multiple pointers in touch screens and the use of speech recognition in some systems, only the hands, eyes, and, occasionally, aural system are considered as participants in interactions, leaving computer users disembodied and incapacitated. Contributing to mounting frustration, perception and interpretation are left entirely to the human user: the human tries to effectively communicate requests, and the computer responds with a predetermined output for the human to interpret.

What would a more satisfying interaction with technology look like? What would be the goal? Interface pioneer Douglas Engelbart suggests that the goal should be to "augment the human intellect." Human-computer interaction research Bilge Mutlu adds the goal of "delivering information at the periphery of attention." An additional goal might be to design emotional experiences for the user. Each of these objectives requires the development of bidirectional interpretation and sensitivity. Computers must be taught to interpret the intentions of a user and to deliver user-centered responses through multiple modalities, sharing the responsibility of communication with the human user as two humans do in conversation. With the development of more robust processing power in the past few years, we have observed a shift toward more intelligent systems that make recommendations to the user through the implementation of machine learning algorithms, but we are still a long way away from the kind of insightful surprises that humans can offer each other in conversation.

The field of human-computer interaction studies the ways in which humans interact with computers and methods for designing better systems with high satisfaction and ease of use. Unlike humans, computers do not possess inherent modalities for interaction. To achieve the bidirectional interpretation described above, it will be useful to consider multiple sensory modalities. This is one of the major challenges in human-computer interaction– building and integrating modalities from scratch. In order to do so, we must quantify complex human behavior in a way that can be reliably interpreted by computers. But which modalities should we consider? And how will we interpret communications through these modalities? We will look to interactions between humans for insights.

Consider the cues available to you in an in-person conversation with another individual. An obvious level of the interaction is the content of words. Beyond that, we may interpret meaning in tone and inflection of a person's voice, facial expressions, and body language (Vinciarelli 1). The most difficult of these to quantify and interpret is probably body language, which includes body movements and posture (Riggio 1). You may have read magazine articles on interpreting body language in the context of dating. For example, if a person lifts his or her shoulder and 'cocks [his/her] head to the side', perhaps that means they are interested in you (Drapkin 1). Such specific, explicit interpretations of body movements and posture are unreliable at best, but there is evidence to suggest that the physical state of a person's body is communicative and meaningful in conversation.

A classic example of the study of body language in conversation is the study of mirroring behaviors, in which individuals non-consciously mimic the physical mannerisms of others in conversation (Chartrand 1). Chartrand and collaborators conclude from a 1999 experiment that this imitation arises from the mere perception of the behavior in others and that it significantly "increases the liking between interaction partners" (Chartrand 1). Research like this suggests that physical cues act as a fundamental element of communication, influencing the content and outcome of interactions between humans.

Extending the hypothesis to cover more specific interpretations of meaning, Rosenthal and Ambady found in their 1993 study on thin-slices of behavior that observers were able to accurately predict the effectiveness of college teachers based on short video clips (under 30 seconds) (Ambady 1). Predictions from short slices of behavior matched evaluations of the teachers at the end of a semester (Ambady 1). A body of research has followed confirming that humans are able to predict the nature of relationships and the intentions of individuals based on thin slices of behavior, with or without words. This interpretation is deeply entangled with biases depending on social context and the appearance of a moving body, as discussed in the *Scope of this Investigation* section of this paper. Nevertheless, studies in this vein suggest that humans of different races and backgrounds are able to quickly interpret intentionality from physical cues in interactions.

Even more strikingly, research in perceptual causality suggests that the interpretation of visual cues like motion occurs at the perceptual level and is not a purely cognitive process (Scholl 305). This means that the interpretation of intentionality from movement is at least somewhat instinctual and hard-wired into the brain. It may also shed light on the difficulty of harnessing the modality of body movements with technology; it is difficult to determine the nature of interpretation that occurs unconsciously. Although the human brain is more adept at interpreting meaning from complex systems of variables, it is reasonable to suggest that a computing system could be developed to emulate human extraction of meaning from movement to augment human-computer interactions with an additional modality.

There is a wealth of evidence in the cognitive and neurological sciences that movement is an important aspect of how humans communicate with one another, but how can we decode this communication so that it can be considered in human-computer interaction? Since the mid-20th century, researchers have approached this problem from a linguistic perspective, building systems for classifying and interpreting gestures as units of language. This results in mostly form-based and direction-based gestural interactions, but what about all of the meaning encoded in a gesture that is independent of its shape? Recently, research in human-computer interaction has begun to consider the perspective offered by the field of dance, an art form that relies upon sequences of body movements to convey relationships and ideas. The studies of choreography and Laban Movement Analysis offer systems for interpreting meaning from a person's physical movements based on quality and context that can be generalized to establish a lexicon of detectable, expressive qualities in human movement that can enhance communication and interpretation on both sides of gestural interfaces.

In this project, we evaluate a specific set of movement qualities outlined in the dance literature – the Laban Action Drive Efforts – as a potential catalog of movement qualities to be used in human-computer interaction. Is the Laban Effort system a useful way of classifying and interpreting conversational gestures for the design of human-computer interfaces? To answer this question, we use a set of pilot studies to assess the following:

1. Can people without any formal dance/movement training identify the Laban Efforts in another person's movement?

If not, it is unlikely that humans rely upon these qualities for interpreting the movements of others, thus the Laban Effort system is unlikely to provide a system for understanding user intention or communication system intention to a user.

2. Are the Laban Efforts present in non-performative expressive movements?

If not, the Laban Effort system is unlikely to aid gestural interfaces in interpreting the emotional state or intention of a user.

3. Is there a correlative relationship between certain Laban Effort qualities and a mover's emotional state or intentions?

If not, this system is unlikely to provide useful classifications of a user's movements for the purposes of interpreting intention or emotional state. It could still provide an additional medium for gestural interface design beyond the existing media of form and directionality, but the ability of that medium to augment the interaction toward the goals discussed above will be limited.

In this thesis, we provide an overview of the history and motivations for the study of movement for the field of human-computer interaction, as well as background information on dance systems for interpreting expressed meaning from movement. We explore the potential applications of classifying movement qualities, as well as precedents from the field. Then, we outline a series of three pilot studies designed to address the above questions, concluding that the Laban Effort system may in fact provide a medium for the design of more satisfying, powerful gestural interfaces.

BACKGROUND

History of Human-Computer Interaction

Although the popularization of gestural interfaces in technology is a recent phenomenon, movement as a medium for communicating with computers is deeply ingrained in the history and development of most of the interfaces we see today. In the following overview, we highlight a few examples of gesture and movement as communicators in the history of the field of human-computer interaction.

Direct manipulation interfaces, in which a user manipulates graphical objects on a screen using a cursor, are the dominant paradigm for human-computer interaction. Between 1949 and 1952, the light pen was invented for users to interact with computers by pointing to objects and drawing directly on the screen (English 1). The first known instance of a completely graphical user interface−*Sketchpad*−was created by Ivan Sutherland in 1963. *Sketchpad* allowed a user to perform actions on objects on the screen with a light pen, “including grabbing objects, moving them, changing size, and using constraints” (Myers 2). It was in 1965 that Douglas Engelbart− famous for his goal to “augment the human intellect”− and his team of researchers at Stanford created the mouse/pointer, which has dominated personal computing interfaces since then (Myers 4). Both the mouse and light pen are examples of interface modalities that interpret the input of a user’s hand movements to trigger commands for a computer to execute. Both can be seen as implementations of deictic (pointing) gestural communication, one of the earliest communicative behaviors observed in infants’ development.

The 1960’s also saw the earliest implementations of gesture recognition systems and touch screens. In 1964, Tom Ellis’s GRAIL (for the Rand Tablet) recognized movements of a light pen to interpret hand-written characters and Teitelman created the first trainable gesture recognition system (Myers 4). In 1965, E.A. Johnson published the first paper on capacitive touch screens, which have enabled the development of modern interfaces with more complex movements than the deictic gesturing of the mouse (Ion 2). Only recently have similar modalities for user input that enable the inclusion of more complex gestural behavior begun to emerge in consumer markets.

Up to this point, we have considered movement as a medium for users to communicate commands to computers, but we have not explored movement as a medium for computers to communicate information to users. As early as the creation of direct manipulation interfaces, graphical objects were used as signifiers for scripts containing commands for a computer, but it was not until 1975 that David Canfield Smith referred to such objects as “icons” (Myers 4). Smith popularized the term in his work at Xerox in the lab that was also responsible for WYSIWYG (What You See Is What You Get), modeless interaction, and the desktop metaphor (Myers 4). This era of development at Xerox PARC labs marks a shift toward more conversational, user-centered interfaces intended to make computers accessible to everyone. With graphics and end-products rendered to the screen rather than code, designers were able to create more user-friendly signifiers, like Bill Atkinson’s famous marching ant pattern to indicate selection (Cook 79). Since then, we have seen movement used as a signifier of icon selection or actions that need to be taken by the user.

The ACM Special Interest Group on Computer-Human Interaction (SIGCHI) was established in 1982 to encourage user-focused research in interface design, fostering collaboration between the fields of computer science, ergonomics, and cognitive psychology

(Roussel 1). With regular meetings and publications, the organization aimed to develop "a science of design seeking to understand and support people interacting with and through technology" (Roussel 1). In the mid-1980's, Microsoft Windows and the Apple Macintosh brought the desktop paradigm and WIMP (Windows Icons Menus Pointers) to consumer markets. The design of interfaces during this time aimed toward "walk-up and use interfaces" focusing on intuitive interactions that were consistent across systems so that novice users could more easily access computing technology (Roussel 1).

In 1983, Richard Bolt's *Put That There* marked the first multi-modal user interface. It used a space-sensing cube to read human deictic gestures in combination with voice commands to manipulate graphical objects on a screen (Bolt 2-4). Though commands were limited to moving and manipulating objects on a screen, the project is a landmark of human-computer interaction as it combines gestural and verbal communication just like human-to-human conversation. In the same year, Myron Kreuger published the book *Artificial Reality* reporting his work on artificial reality lab *VIDEOPLACE*. *VIDEOPLACE* was a sort of shadow world, in which silhouettes of different users could be rescaled to interact with one another through gesture (MediaTube). The system tracked hands, fingers, and other body parts to recognize movements and produce appropriate graphical and auditory output, more or less obeying (though augmenting) the physics of the natural realm (Krueger 1). This is one of the earliest systems that successfully facilitated humans interacting with other humans through technology in a way that would not otherwise be possible (MediaTube). It marks a shift in our thinking about computers as sophisticated calculators and word processing devices toward media for new and satisfying human experiences.

By the early 1990’s, personal computers had gained a popular presence in homes, but daily usage was still challenging and often unsatisfying. Some designers began to consider intelligent interfaces that would use artificial intelligence to better interpret user actions (Roussel 2). Other designers turned to participatory methods that involved users in the process of creating interfaces (Roussel 2). New design frameworks like situated action, distributed cognition and activity theory also emerged as interface creators began to see user actions as part of a system (Roussel 2).

In 2016, we stand at the precipice of the integration of design frameworks and approaches that have been separate for the past few decades. Fast computing systems and network communication have made way for the popularization of machine learning techniques. Connectivity and globalization made possible by the development of internet infrastructure and smart computing devices have increased the relevance of social contextualization of user actions. The availability of sensors in smart devices has opened up the potential for new interface modalities. Simultaneously, a shift toward holistic thinking about human health and developments in neurological and cognitive sciences are driving interest in embodied interfaces.

The field of human-computer interaction is now uniquely positioned to realize visions that have been simmering since the earliest days of computing. The goal of creating more satisfying, natural interactions between humans and technology can finally be approached by emulating satisfying, natural interactions between humans. As we have discussed, seamless communication between humans is enhanced by cues delivered through posture and gesture, and work is needed to integrate these modalities into everyday human-computer interfaces. The medium of movement has potential for both interpreting a user’s intentions and communicating information back to a user. If we could reliably and explicitly connect meaning to movements, we could create surprisingly natural interfaces using non-conscious or intuitive communicative gestures as both input and output. That stated, the challenge of extracting meaning from movement is complex and has a history of its own.

History of Movement Analysis

Thinkers and philosophers have been interested in gestural expression since antiquity. As far back as the Roman Empire, academics have studied the use of gesture in rhetoric (Kendon 154). A number of investigations of gestural communication were created from the 17th through the 19th centuries in Europe, including a manual for notating and interpreting gestures by Bacon in 1875 (Kendon 155). As linguistic gesture expert Kendon explains, "the main concern was to lay down the rules and principles that were to be followed in the use of gesture, and to provide description and instruction so that the pupil could acquire a repertoire of specific actions that were to be used in particular ways and which were ascribed specific meanings" (Kendon 155). Though our purposes have shifted away from teaching effective techniques for gestural communication, current studies of gesture in linguistics and human-computer interaction share the idea of "gesture as a 'natural' form of expression," in Kendon's words, and communication of an individual's inner intentions (Kendon 155).

As Kendon notes, the late 19th century marked a decline in the study of gesture in Western linguistics, but interest in communication processes sparked by information theory and cybernetics in the World War II era reignited the study of gestural communication (Kendon 160). Notably, in the 1940's, Efron studied gestural communication as a product of environment and race (Efron 1), distinguishing between the preparation, action, and retraction stages of a gesture in an effort to classify movements to analyze cultural differences in non-verbal communication (Zhao 9). A few other researchers, including Birdswhistell and Ekman, hinted at the relevance of developing a framework to study gesture, but it was not until the 1970's that new systems for classifying gestures began to emerge in linguistics and psychology in the work of Kendon, McNeill & Levy, and Rime & Schiaratura (Zhao 9).

Movement Analysis in Performing Arts

By the time the discipline of linguistics began its exploration of gesture, practitioners and teachers of physical performance had already begun to create taxonomies of expressive movement. In the mid-19th century, Delsarte created a system of movements and postures for actors to express their inner emotional truths. Historian Warman explains that in the system, "every expression of the face, every gesture, every posture of the body corresponds to, or is but the outward expression of, an inner emotion or condition of the mind…" (Warman 23). Again, Delsarte's system was prescriptive; he aimed to teach performers to better express their inner experiences, although he intended for his system to be honestly expressive rather than manipulated and imposed.

In the 1920's, dancer and choreographer Rudolf von Laban began his exploration of classifying movements from a more descriptive standpoint (Trinity Laban). In addition to his famous notation system, now obsolete with the wide availability of video, Laban and his colleagues− notably Lisa Ullmann, Irmgard Bartenieff, and Warren Lamb −developed a framework for describing shape, quality, spatial use, and body involvement of movements (Trinity Laban). This system considers not only *what* movement is occurring, but *how* the movement is being executed. The *how* is particularly useful in interpreting the intention driving a movement.

Though the Laban system for Movement Analysis has existed since the 1940's and Delsarte's system has been published since long before, neither Laban or Delsarte are included in Kendon's often cited 1981 essay *The study of gesture: Some remarks on its history*. Recent efforts to connect gestures to affective meaning in the field of human-computer interaction have begun to consider the Laban system as a guide for recognizing emotionally communicative qualities. However, little work establishing the relevance of this system to the linguistic understanding of gesture in conversational settings has been done. Moreover, this system was not well considered in the early studies of Kendon and his contemporaries that laid the groundwork for defining and classifying gesture in language acquisition and thus human-computer interaction.

Defining a Gesture

The problem of defining a gesture is essential to extracting meaning from movement-based communication and designing systems that use this modality for communication between humans and computers. In this project, we will seek the definition for gesture that best suits the goal of interpreting intention from movement. The most obvious question to be answered is, of course, "What is a gesture?" Merriam-Webster defines a gesture as "a movement of your body (especially of your hands and arms) that shows or emphasizes an idea or a feeling" ("Gesture"). In the lineage of Kendon, McNeill's definition of a gesture includes "movements of the arms and hands which are closely synchronized with the flow of speech" (McNeill, 1992). In the field of dance, movement is generally seen as a medium of expression that can stand alone without augmentation, but which can be complemented by sound or speech (Ambrosio 21). The concept of gesture in Laban's system, for example, includes any movement that does not involve the transfer of weight (Griesbeck 1). For the purpose of designing movement-based systems for human-computer interaction, I suggest that we adopt and expand the Laban definition of gesture to answer two important refining questions:

First, what body parts are involved in a single gesture? The Laban definition excludes body parts that are not actually moving, but I suggest that the postural orientation of peripheral body parts can alter the intention communicated by the gesturing limb. The Laban system considers non-moving body parts that are active in communication by creating a separate category for Posture, subsequently interpreting meaning from the combination (or Merger) of Posture and Gesture (Davies 66). This is an effective approach, but I propose the inclusion of stationary body parts in our concept of gesture – positions of non-moving parts can serve as features in machine learning algorithms that can interpret movements. However, we must determine a system for excluding those parts of the body that are not active in the communication. The accurate classification of gestures by machine learning algorithms suffers in the presence of extraneous features. We can look to insights from human interpretation of movements to help solve this problem.

Second, when does a gesture begin and end? In his early studies, Kendon attempted to determine the timing of gestures by having users encode videos. This exploration led to his theory that "the stroke of [a] gesture phrase occurs simultaneously with (or slightly preceding) the nucleus of the tone unit" (Zhao 10). I suggest that we expand Kendon's work to include movements that fall outside of traditional linguistic gestures coupled with words. I also suggest that we expand our temporal consideration of gesture to better contextualize a single action within an extended interaction. Not just theoretical, the question of timing is technical in nature as well: a machine learning system must manage large streams of data and must segment time in order to choose which data is relevant. This is known as the time-segmentation problem in gesture recognition and is ubiquitous in implementations of gesture recognition systems. Many teams have developed ways of handling the problem, but I suggest we explore the perspective offered by humans interpreting meaning and quality from movement for possible new solutions. This will be challenging as these processes are not all conscious, but the potential insights from such an investigation are quite promising.

Gesture Classification Systems

Having established the relevance and fundamental challenges of designing movement-based systems for human-computer interaction, we will examine a few different taxonomies for gesture classification from different disciplines. As discussed above, philosophers have created taxonomies of expressive gestures seeking to better understand and leverage non-verbal communication for centuries. We will investigate the systems created as part of the surge of interest in gesture in language acquisition in the latter half of the 20th century.

Gesture Classification in Linguistics

Gesture researcher Efron, widely considered the grandfather of gesture classification in linguistics, set out to understand the differences in gestural communication of different ethnic groups. In his investigation, he laid the groundwork for linguistic researchers that followed. As mentioned above, he established the stages of a gesture as preparation, stroke, and retraction, later adopted by Kendon (Zhao 9). He also defined emblems in gesture: as interpreted by Johnson and colleagues, “emblems were movement patterns that had a precise meaning.” Efron believed that glossaries of emblematic gestures could be created for specific ethnic groups, and he created one such glossary for immigrant Sicilians in the United States

(Johnson 1). This work guided Saitz and Cervenka in their creation of similar glossaries for Columbians and Americans.

It also influenced Ekman & Friesen in their system for classifying nonverbal behavior, which distinguishes between "facial expressions of emotion, regulators, adaptors, illustrators, and emblems" (Johnson 1-2). According to Ekman and Friesen (Ekman 39-47):

- Regulators are movements that accompany speech to facilitate the flow of conversation and ideas as in head nodding or lifting a finger.
- Adaptors (also called manipulators) are non-conscious movements that coexist with speech to adapt to the conversational situation, such as scratching one's face or adjusting one's clothing.
- Illustrators are gestures with co-occur with speech to illustrate the idea being expressed. This could include indicating the size or shape of an object with one's hands or deictic gestures.
- Emblems are non-verbal signals that can be directly translated into words, such as the *ok-symbol* or *thumbs up*. These are culturally specific.
- Emotional expressions are signals of an emotional experience. These could include facial expressions, postural shifts, or any other emotionally expressive movement.

In a similar approach to that of Ekman and Friesen, Kendon attempts to extract meaning from gesture by interpreting its conversational context. However, rather than classifying gestures into categories that serve distinct conversational purposes, Kendon places gestures on a continuum ranging from the least linguistically significant to the most linguistically significant movements (McNeill, 2006 58-61). In line with his studies that tie gesture to speech temporally, Kendon arranges gestures into classes according to their interchangeability with words as follows:

➔ Presence of language properties and social regulation increase ↑

Gesticulation ➔ Language-like Gestures ➔ Pantomimes ➔ Emblems ➔ Sign

➔ Obligatory presence of speech and idiosyncratic gestures decrease ↓

Figure 1: Kendon Continuum

Gesture linguist McNeill explains that with movement from left to right on the continuum, "(1) the obligatory of presence of speech declines, (2) the presence of language properties increases, and (3) idiosyncratic gestures are replaced by socially regulated signs" (McNeill, 1992 37). For example, a *thumbs up* would fall toward the sign end of the spectrum as it has a specific meaning (within particular cultures) that can be accurately interpreted without accompanying speech. An extension of the hand forward with the palm facing upward in the middle of a sentence, on the other hand, would fall toward the gesticulation end of the spectrum as a specific meaning cannot be gleaned from the movement alone.

Informed by the work of their predecessors, McNeill & Levy also conform to the viewpoint that movements must be interpreted in conjunction with co-occurring speech. Their widely adopted system for classifying gestures further dissects the gesticulation area of Kendon's continuum into the following dimensions:

- Iconic: "Such gestures present images of concrete entities and/or actions. For example, appearing to grasp and bend back something while saying 'and he bends it way back.' The gesture, as a referential symbol, functions via its formal and structural resemblance to event or objects."

- Metaphoric: "In a metaphoric gesture, an abstract meaning is presented as if it had form and/or occupied space. For example, a speaker appears to be holding an object, as if presenting it, yet the meaning is not presenting an object but an 'idea' or 'memory' or some other abstract 'object.'"
- Deictic: Pointing to indicate location, usually but not always with a finger or hand. Location can be either immediate or metaphoric.
- Beats: Rhythmic hand movements accompanying speech, "signaling the temporal locus of something the speaker feels to be important with respect to the larger context." (McNeill 4)

The work of McNeill & Levy, Kendon, Ekman & Friese, and Efron provide tools for analyzing the meaning of movements in their conversational context. In order to more closely consider natural, effortless forms of nonverbal communication for human-computer interaction, we should also investigate the cognitive science perspective on movement as a medium for communication. We are interested in both the processes by which gestures are interpreted and the processes by which they are produced.

Gesture in the Cognitive Sciences

We begin our investigation of the perception of meaning from movement with cognitive science pioneer Michotte's landmark work on perception of causality from moving visual stimuli. By showing animations of moving geometric shapes and asking subjects to report percepts, Michotte demonstrated that causal relationships were almost universally perceived by observers from simple movements (Scholl 301). Michotte's work focused on "discovering the spatiotemporal parameters that mediate these causal percepts, such as the items' relative speeds, speed–mass interactions, overall path lengths, and spatial and temporal gaps" (Scholl 301). As Scholl and Tremoulet suggest, the most important contribution of Michotte's work may be the knowledge that there are "specific conditions" of movement that lead to the perception of causality (Scholl 301). Extending this work, Heider & Schimmel use similar methods to demonstrate that humans are likely to interpret personality traits and emotions– even genders and specific intentions (Dittrich 254) – from the movement of abstract objects in animations (Scholl 302). This evidence suggests that movement itself is a medium by which affect, personality, and intention are communicated. Similar research like that of Bassili supports that movement patterns are also indicators of animacy of an object (Scholl 303-304).

Though it is clear that movement plays a role in communication and perception of intention between humans, only recently has research begun to shed light on the nature of processing of these stimuli. In this discussion, we must distinguish between perceptual processes – low level construction performed by the visual system – and cognitive processes – high level processes used to interpret the pre-processed constructions of different sensory systems (McLeod). Scholl and Tremoulet suggest that instances of interpretation of causality, animacy, and intentionality from simple movements "have the character of visual percepts yet involve what are traditionally thought to be higher-level concepts" (Scholl 305). They conclude that evidence is "consistent with the view that such phenomena reflect primarily perceptual and perhaps modular processing, and at a minimum are very different (and can be dissociated) from high-level cognitive judgments of the existence of causality or animacy" (Scholl 304).

We can also distinguish between top-down and bottom-up models of perception. In bottom-up models, sensory stimuli are processed iteratively, one piece at a time, with increasing complexity at each level of processing to construct overall meaning of the stimuli (McLeod). In other words, the parts are processed to construct the whole. In top-down models, information about the context of the stimuli inform the interpretation of each part at every stage of processing (McLeod). In other words, the context of the whole informs the analysis and interpretation of the parts, including which parts should be attended to. In the lineage of Michotte, Dittrich & Lea have conducted studies to assess perception of intentionality and animacy of a uniquely moving letter amongst a sea of other less directly moving letters. They hypothesize a combination of bottom-up and top-down processing: "The immediate impression of intentionality (or causality) is given by a 'bottom-up' process of selecting specific motion features, and at a later stage these are visually encoded and conceptually integrated in such a way that intentional percepts are activated through a 'top-down' process" (Dittrich 254). Based on their results, they conclude that, "the perception of intentionality can be a relatively immediate, bottom-up process, probably occurring quite early in the visual processing" (Dittrich 255). However, they note that in more complex behaviors like speaking, top-down cognitive processing also plays a role (Dittrich 255).

It is relevant to note that Dittrich & Lea focused on assessing intentionality from interactions between a target letter and goal letter. The idea here is that the interaction is the indicator for intentionality. When the goal letter was made invisible, the interpretation of intentionality became less accurate, but only slightly (Scholl 304), indicating that the movements of the object itself, removed of any context, were communicative to some degree of intentionality. This suggests that movements and their execution are independently communicative, supporting the investigation of the meaning of individual movements in conversation and conversational interfaces.

The cognitive sciences also offer theories on the onset of communicative movement in conversation on the part of the doer. At this point, two opposing models for understanding the onset of a gesture exist. In coactivation models, speech and gesture arise from the same impulse or idea. A person first experiences a thought and the mind channels the outward expression of the thought through different media of speech and movement simultaneously (Zhao 16). In competition models, speech and gesture compete for attention and distract the doer from one another. In this view, attention is a limited, finite resource that must be divided amongst different cognitive tasks. Attention that is dedicated to speaking detracts from the available resources for moving and vice versa (Zhao 17).

Understanding the cognitive processes associated with multi-modal expression is important to interpreting and contextualizing expression through a single modality. Is it appropriate to ascribe meaning to a movement based on cues from other media for expression? Is it appropriate to ignore context provided by those media? Would it be appropriate to design systems for human computer interaction that rely on multiple modalities for communication? Further attention is needed to adequately investigate this topic. This thesis draws from the field of dance to provide tools for interpreting movement independent of other co-occurring forms of expression.

The linguistic models for classification of gesture discussed up to this point give great consideration to the relationship between gestures and the words they complement. Shape is considered in deriving meaning from emblematic gestures or in conjunction with words in metaphoric gestures. Location in space is considered in interpreting deictic and self-referential gestures. Timing in conjunction with words is considered in decoding beat gestures. However, the quality of gestures is not well considered in the linguistic approach to classification. The manner in which a body part moves through space over time is considered more thoroughly in the field of dance in a system called Laban Movement Analysis.

Gesture Classification in Laban Movement Analysis

Laban Movement Analysis provides a system for describing characteristics of individual movements and phrases according to four Affinities: Shape, Effort, Body, and Space. Shape is primarily concerned with position and pathway (change in position over time) of body parts (Konie 2). The Shape of a movement can be described as arc-like (curvy) or spoke-like (linear). Spoke-like movements tend to be more direct and are more likely to indicate aggression or urgency. The Shape of a movement can also be rising/sinking, spreading/closing, or advancing/retreating (Konie 2). This terminology for describing Shape inherently encodes emotional and intentional interpretations.

The Effort Affinity is intended to describe the differences between movements that are mechanically similar but qualitatively and expressively different. Is a movement sharp or soft? Light or Heavy? The quality with which a movement is performed in important in interpreting the mover's emotional state or intention. In order to decode qualitative differences, the Laban system considers four factors: Space (Direct or Indirect), Weight (Heavy or Light), Time (Quick or Sustained), and Flow (Free or Bound) (Konie 3). Because the Laban Efforts play a significant role in this research, it is important to gain a sense for each of the above

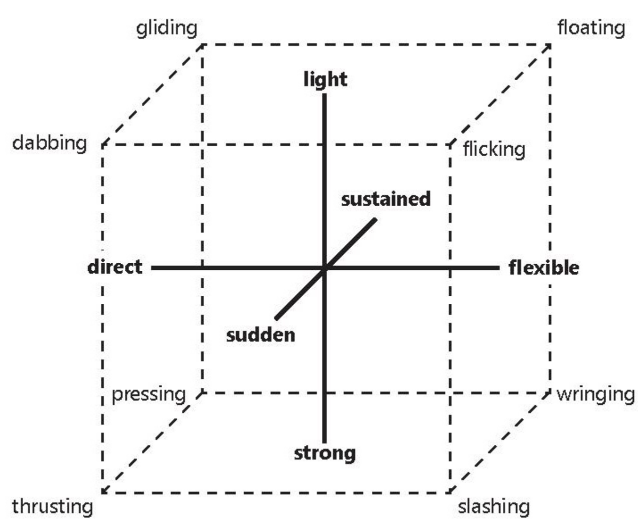

Figure 2: Laban Effort Graph (Cooba)

factors:

1. The Space factor describes how an action is situated in space. An Indirect action may meander through space or change in spatial intention over the course of a movement, where a Direct action has a clear spatial pathway and intention that is consistent over its duration and is more likely to feature a clear stop.

2. The Time factor describes how a movement behaves in time. In the Laban system, a movement is either Quick or Sustained, meaning that it lasts for a short or drawn out time. This is obviously dependent upon the definition of a scale or point of reference, which is usually defined by the gestural phrase in which a movement occurs.

3. The Weight factor describes the physical effort that goes into a movement and the grounding with which the movement is performed. A Light movement generally involves less resistance and is supported by less power than a Heavy/Strong movement.

4. The Flow factor describes the flow of energy and momentum within movements. For example, a Free Flow movement is characterized by conserved speed and fluidly transformed direction within its momentum, where a Bound Flow movement is characterized by clear and intentional changes in speed and direction (Konie 3).

Each of these factors represents a continuum that must be calibrated to each individual mover and situation, but a value assignment for each factor can aid in qualitatively describing a movement. Laban articulated eight specific Efforts in the Action Drive: Slash, Dab, Press, Wring, Flick, Glide, Punch, and Float, each a combination of specific values for the Time, Space, and Weight factors visible in Figure 3 and in Table 2 (Laban). These Efforts are particularly useful in connecting intention to the quality of a movement as their titles communicate both quality and aim. Diagrams approximating how the same movement might look if performed with each of the Laban Effort qualities are shown in Figure 3. Length and width of arrows indicate duration and strength of movement. Slight variations in pathway might demonstrate an Indirect approach to space, but these variations in the arrows mostly indicate speed over the course of the movement. Size and shape of arrowheads indicate the quality of the stop, where shallow, wide arrowheads indicate clean stops.

Figure 3: Laban Effort Diagrams

Effort	Time	Space	Weight
Dab	*Quick*	*Direct*	*Light*
Glide	*Sustained*	*Direct*	*Light*
Press	*Sustained*	*Direct*	*Heavy*
Slash	*Quick*	*Indirect*	*Heavy*
Wring	*Sustained*	*Indirect*	*Heavy*
Flick	*Quick*	*Indirect*	*Light*
Float	*Sustained*	*Indirect*	*Light*
Punch	*Quick*	*Direct*	*Heavy*

Table 1: Laban Effort Categories

In the Body Affinity, we are concerned with the patterning of connectivity between body parts. Bartinieff outlines 6 fundamental patterns of Total Body Connectivity:

- Breath: relationship between a movement and the breath of the mover
- Upper-Lower: relationship between regions above and below the waist
- Core-Distal: relationship between the core and distal points on the body
- Head-Tail: relationship between the top and bottom ends of the spine
- Body-Half: relationship between right and left sides of the body
- Cross-Lateral: relationship between one quadrant of the body and its diagonally opposite quadrant (Konie 4)

A thorough investigation of the use of the body in a movement also considers the point of initiation for a movement and the sequencing of body parts involved (Konie 4). A movement that is initiated by the core may indicate an inner compulsion rather than an externally motivated drive, for example. Or a movement that is sequenced simultaneously (all parts shift at once) may communicate directness of intention, where a movement that is sequenced differently may communicate less commitment to accomplishing a goal or acknowledgement of obstacles.

The final Affinity for consideration is Space. In the Space Affinity, LMA defines the kinesphere as the sphere that marks the boundary of reach of a person's body in three-dimensional space (Konie 4). A movement can be central, radiating from the center of the kinesphere outward, peripheral, moving along the edges of the kinesphere, or transverse, slicing non-radially through the kinesphere (Konie 4). The Space Affinity also dictates the division of space into vertical, sagittal, and horizontal dimensions and planes similar to those of Cartesian coordinates and the dissection of movement into directional pulls (Konie 4). The LMA methods for dividing space can be useful in determining the intention of a movement. For example, a movement that occurs in the horizontal plane might communicate a relationship between two points in time or space, where a movement in the sagittal plane might communicate ambition or aggression.

The Laban system for movement analysis outlines a variety of communicative features of movement that can be extracted and interpreted separately from any accompanying speech. The use of such a system could enable the interpretation of movement independently of any other modalities, which could be useful in a computing system in which the integration of different modalities is complex and expensive. It also opens up the possibility of interpreting non-conscious communications of the state of a user of a system. There are many applications in which monitoring a user's emotional state could aid in better meeting the needs of the user, such as monitoring the care of an individual in the context of assistive technology. The field of dance also provides tools to enable the consideration of features of previous movements in the interpretation of features of new movements. In other words, a movement can be contextualized relative to other movements rather than relying on separate modalities.

Interpreting Movement in Context

Choreographic Approach

More broadly, the study of dance and choreography provides a myriad of tools for interpreting movement in context. The role of a choreographer is to design a sequence of movement events that are in some way significant or meaningful to an observer. As choreographic scholar Jacqueline M. Smith-Autard describes, the composition of a dance is "the moulding together of compatible elements, which, by their relationship and fusion, form an identifiable 'something'" (Smith-Autard 3). This is not necessarily accomplished in the form of narrative and literal meaning, but often in the form of an emotional arc or the expression of an abstract relationship between ideas (Smith-Autard 5). Regardless of the choreographer's specific intention, he or she composes movements considering both content – movement vocabulary– and context – construction of the overall work – to realize his/her specific goals (Smith-Autard 3). The choreographer makes choices about *what* movements are performed by *who, when*, and *how*. The choreographer develops concepts by finding variations on previous movement ideas, investigating how subtle changes alter the meaning of movements (Green ix-x). This development reveals relationships across space and time in the same way that movements in daily life reveal relationships.

Parviainen and collaborators argue that the sensibilities of a choreographer should be utilized in user experience design to consider experiences in context. They suggest that movements should "be understood as dynamic moments of embodied presence belonging to an experiential chain of different movements which has its own significance as a whole" (1). Proposing a framework for dissecting events, Parviainen asserts that dance provides tools for understanding micro, local, and global context of interactions. The research team defines micro level of context as "improvised or automatic and habitual movement patterns which people make in their ordinary way of life" with their kinespheres (Parviainen 2). Local-level consideration of context is defined as the connection between the uses of technology and other activities, including "relations we create by using devices" (Parviainen 2). Macro-level context includes "connections and relations in which we exceed our own physical limits" (Parviainen 3). For the purposes of developing gestural interfaces, we will mostly be concerned with mico-level contextualization of movement as informed by dance. What is the relationship between a movement and the preceding movements? Is the current movement a repetition or variation of something we have seen before? We would be amiss to ignore the broader contextualization of movement, however, in a design paradigm that is largely concerned with holistic thinking. As designers have come to view the context in which an action occurs as equally important to the action itself, it is important for gestural interfaces designers to develop tools for contextualizing movement.

Contextual Design Frameworks

By the early 1990's, several design frameworks had emerged in response to frustration with inadequate human-computer interactions and shifts in the cognitive sciences. Situated action, distributed cognition, and activity theory are approaches to understanding actions of an individual in context. Situated action (activity) is the theory that any individual action must be understood in relation to the specific situation in which it occurs. As Clancey explains,

> Situated activity is not a kind of action, but the nature of animal interaction at all times, in contrast with most machines we know. This is not merely a claim that context is important, but what constitutes the context, how you categorize the world, arises together with processes that are coordinating physical activity. To be perceiving the world is to be acting in it--not in a linear input-output relation (act>observe>change)--but dialectically, so that what I am perceiving and how I am moving co-determine each other (Clancey 95).

In the situated action approach, an individual's perception of a situation cannot be separated from the actions chosen by the individual. Rather, perception and decision-making co-occur in conversation with one another. Distributed cognition, like situated action, is concerned with the relationship between a subject and his/her environment as a way of understanding actions, but in distributed cognition, the actor cannot be separated from his or her environment. Rather, the system in which the actor resides is responsible for the actions taking place. The approach "focuses mainly on three kinds of distributed cognitive processes: social processes: across the members of a social group; processes related to material environment: across internal and external (material or environmental) structures; and distributed cognition in time: how the products of earlier events can transform the nature of later events" (Riva 51). Activity theory is similar in that it views a system as a whole as responsible for the action, but in activity theory the action cannot be separated from the system. As Nardi explains,

> Activity theory proposes a very specific notion of context: the activity itself is the context. What takes place in an activity system composed of object, actions, and operation, is the context… People consciously and deliberately generate contexts (activities) in part through their own objects; hence context is not just 'out there… Context is both internal to people—involving specific objects and goals—and, at the same time, external to people, involving artifacts, other people, specific settings. The crucial point is that in activity theory, external and internal are fused, unified (Nardi 38).

Situated action, distributed cognition, and activity theory provide designers with a way of considering interactions within context, so that specific instances of interactions can be considered to create more broadly functional systems. We can observe how these abstract ideas can be applied to the design of computing systems. For example, design researchers Uden and Helo outline a framework for designing "context-aware" mobile applications considering factors like the size of a mobile screen, the changing environment of use, and the specific needs of individual users (Uden 2). In the same paper, they describe the effective design of shallow navigational structures in websites considering the optimization of cognitive load for users (Uden 4). However, they also note that, "Computers are currently not able to take full advantage of the context of human-computer dialogue," and that "by improving the computer's access to context, we can increase the richness of communication in human-computer interaction" (Uden 4). The technical challenges posed by creating gestural interfaces, in conjunction with limited knowledge regarding the meaning of body movements, have narrowed the potential contexts for consideration in their design, preventing the application of contextual design approaches to movement-based interactions.

Problems with Current Gestural Interfaces

The necessity of special hardware for sensing, tracking, and interpreting movement data confines gestural systems to a context in which the hardware must be consciously activated. For example, to interact with the Microsoft Hololens, a person must put on the headset, adjust it, and activate a program. This mitigates the possibility of interacting with such systems naturally within the flow of everyday life. Moreover, existing frameworks for interpreting gesture in linguistics are mostly concerned with understanding movement in the context of speech and based on form, limiting our ability to interpret movement in other contexts. In an article in *Smashing Magazine*, author Chris Noessel compiles a list of commonly used gestures in interface design: Wave to activate, Push to move, Turn to rotate, Swipe to dismiss, Point to select, Pinch and Spread to scale (Noessel 5). While many of these movements are intuitive, each one can be traced to one of the early human-computer interaction concepts: pointers, direct manipulation, and emblems, and these concepts reflect the linguistic approach to understanding gesture. Although this approach is certainly valid, this set of movements only comprises a small subset of the communicative movements people engage in on a regular basis. The absence of frameworks for interpreting movement as more than an accompaniment to speech limits our ability to harness the previously discussed contextual design frameworks in the context of gestural interfaces.

Fortunately, leaders in the field of gesture-based human-computer interaction are thinking about the problem. Gesture researcher Zhao notes four major focuses for future gesture-based HCI research based on the work of human-computer interaction expert Cassell: Coarticulation (time segmentation), Spatialization (integrating movement systems into spatial environment), Selection (creating “metaphoric gesture[s] that might be associated with an abstract concept”), Expression (modifying movement quality to express mood or temperament) (Zhao 24). Advances in each of these areas will provide better tools for understanding and designing gestures in context so that they can be better utilized as a medium for communication. It is possible that the body of knowledge in the field of dance can offer tools to aid in this contextualization. We can also look to the integration of movement into screen-based interfaces for insights into reducing the separation between movement and other activities.

Survey of Applications for Movement Quality in HCI

Movement as Communicator On-Screen

Researchers since the 1970’s have been concerned with the use of movement in the presentation, interaction and manipulation of signifiers on computer screens. The marching ant signifier for selection and jumping icons for alerts provide examples of the successful integration of movement as a medium for communication into a screen-based workflow. More recently, Mutlu and colleagues have begun to investigate the design of movement on the screen to elicit affect and/or communicate emotional intentions.

Informed by the work of Michotte and colleagues in the cognitive sciences, Mutlu’s team “iteratively designed and implemented a public social interface using abstraction and motion as design elements” to “[communicate] simple social and emotional content” (Mutlu

1). As they explain, “A substantial amount of work in Human-Computer Interaction borrows from biological and natural materials for the design of interactive displays that deliver information on the periphery of attention” (Mutlu 2). As the cognitive science literature suggests, movement is a medium for communication that is processed “on the periphery of attention.” Mutlu’s team were able to successfully create eight out of ten motion patterns with statistically significant consistent emotional interpretations (Mutlu 4), noting that the interface changed the social dynamics of the room and that people interpreted the interface both individually and collaboratively (Mutlu 7). If designers had a stronger understanding of how movement quality is communicative or how movements are contextualized on a larger scale, movement of elements on a screen could be designed to more fluidly communicate intention or emotional state. For example, an icon might move with a more aggressive movement quality to indicate that an issue must be attended to urgently, or a the appearance of a message box suggesting actions to a user might use a more gentle movement quality so as to gain the user’s attention without interrupting the user’s thought process. This knowledge might be especially relevant to creating more, communicative, relatable virtual characters that could express social and emotional responses to users’ actions (Vala 1). Such characters are often employed to guide users through interactions with smart homes, installations, and other assistive technologies. The applications would reach traditional screen-based computing systems and touch-screens, as well as screens in nontraditional locations.

Movement as Communicator Off-Screen

With the recent advancement and availability of new hardware such as the Microsoft Kinect, Leap Motion, and smart phones, as well as robots, we can begin to consider movements off the screen as media for communication in human-computer interaction. In this new modality, possibilities for interaction include movements required of users to interact with a system, the interpretation of non-conscious movements performed by users to infer intentionality, and movements of the physical representation of the system as communicators (robots and other moving hardware). Particularly in the case of designed movements for interaction, shifts in scientific understanding of the experience of moving should guide the approach taken by interface creators.

Kinesthetic Interfaces

With new hardware for interacting with technology, new considerations for the design of user experiences arise. Technology can influence the state of a user through content, ease of navigation, and intuitiveness just the same, but now the user can also be influenced by the physical movements required to interact with the system. This is both an avenue full of possibility and a new challenge.

In conjunction with the movement toward more holistic approaches to understanding human behavior, cognitive and neural science research provides substantial evidence of a link between the sensation of movement and emotional state. In a study published in 2010, Casasanto and Dijkstra examined the relationship between simple, meaningless motor tasks and emotions. They found that when subjects were asked to move marbles downward from a higher bin to a lower bin, they were able to recall memories with negative emotions faster than those with positive emotions. When given emotionally neutral prompts for memories, they were significantly more likely to recall emotionally negative memories (Casasanto 1). More popularly known is Amy Cuddy’s research on power-posing, which indicates that spending two minutes in a powerful position raises testosterone levels and lowers cortisol in the brain, enhancing confident functioning in social situations. She has found that the converse is also true (Cuddy). This research suggests a link between proprioceptive and equilibrioceptive information and human emotion, supporting conjecture that the physical state of a body affects an individual's mental and emotional states.

In this new paradigm, the state of the physical body is now entangled with the state of a person's mind, and a new context-based design framework has emerged to support this understanding. The embodied cognition theory, "underlines the central role of body in shaping the mind" (Riva 51). Specifically, the mind has to be understood in the context of its relationship to a physical body that interacts with the world. Hence, human cognition, rather than being centralized, abstract, and sharply distinct from peripheral input and output modules, has instead deep roots in sensorimotor processing" (Riva 51). This approach is reflected in the design of new gestural interfaces, including interactions with the smart phone.

Several scholars and designers have already begun to consider the use of Laban Efforts in the design of gestural interfaces. Focusing on touch screen interactions, UX designer Traci Lepore classifies the slide-to-unlock interaction on the iPhone as a Laban Glide, noting that the gesture is "focused, easy, and isolated" (Lepore 2). Based on the results of the pilot studies in this thesis, the gliding action may be associated with a sense of ease and accomplishment, and this affect-Effort association may contribute to the success of the design. The focus of this paper is to evaluate the validity of this analysis. Lepore also notes the successful use of the Press to move icons around on the iPhone screen, which is consistent with the effort required to move objects around in the physical world. As a less successful employment of Laban Efforts, Lepore notes the Flick needed to shake the iPhone to undo actions (Lepore 2). As Lepore explains, the Flick is a Light movement, which requires little effort to accomplish, where undoing a previous action requires more effort. She suggests that a heavier movement quality like Slashing might be more appropriate for this interaction (Lepore 2).

Dance and technology scholar Kate Sicchio highlights the potential, perhaps inadvertent, emotional effects of such kinesthetic interfaces, citing the Tinder Flick motion (Sicchio 22-24). Sicchio suggests that the experience of the Laban Flick Effort is carefree, much as the experience of flipping through dating profiles on Tinder can be shallow and cursory (Sicchio 22-24). This evaluation is consistent with criticism of Tinder's influence on the modern dating world, in which people increasingly view potential mates as disposable (Sales 1). This criticism can be traced to the actual content and social constructs of the app, but it is possible that the physical experience of swiping through Tinder influences the way users feel about other users (Sicchio 22-24). With greater awareness of the connections between movement quality and affect, we can design kinesthetic experiences for users that are more consistent with the goals of an interface.

The consideration of kinesthetic experience as output of a system to the user has the potential to create impactful experiences, but designers are challenged to consider ergonomics to avoid fatigue (Danielescu). This requires the development of a diverse body of gestures for interacting with technological systems, often addressed through elicitation studies, in which users are prompted to create gestures to accomplish certain tasks (Danielescu). Researchers tackling this problem face a limit to the creativity and variety of gestures created. I suggest that a taxonomy of movement qualities could provide a new layer of complexity for creating different detectable, gestures without expanding the range and energy needed to perform the gestures. It is also possible that such a taxonomy could aid designers in creating variations in gestures that align well with the user's intentions or elicit satisfying, appropriate emotional responses to actions.

Social Robots and Virtual Companions

As the presence of robots expands beyond the realm of industrial settings, it is increasingly important that robots become capable of understanding and engaging in social interactions (Castro-Gonzales 1). As robotics researcher Alvaro Castro-Gonzales and his collaborators suggest, robotics designers aim to "[create] the illusion of animacy" in creating a robot by considering "its size, its appearance, its responsiveness to stimuli, the appropriateness of its responses and the diversity of its behavioral repertoire…" (Castro-Gonzales 1). To investigate variations in movement style and appearance of robots as they affect human-robot interactions, Castro-Gonzales and his team observed humans interacting with a robot in a game of tic-tac-toe with different settings and constraints. They varied the amount of the robot that was visible to the player to investigate anthropomorphism and they varied the robot's movements between smooth and mechanistic patterns, measuring "likability, animacy, unpleasantness, and trustworthiness" (Castro-Gonzales 2). They found that smooth movements were more likeable and animate for both the anthropomorphic robot and the lone robot arm (Castro-Gonzales 8). However, the smoothly moving full-body robot was considered more unpleasant than the mechanistically moving full-body robot, where the movement style did not seem to affect assessments of unpleasantness in the single robot arm (Castro-Gonzales 8). This research suggests that more human-like movement will contribute to greater likeability and animacy of social robots, but considerations of the appearance of the moving robot are necessary to have the desired effect. It also indicates that the appearance of a moving body cannot be fully separated from the movement of the body itself in human interpretation. This must be considered in both the design and study of movement-based forms of communication, but the aforementioned studies on the movement of abstract objects still support the concept of movement as an independent communicator.

Similar research on movement as a communicator in social interactions between humans and physical hardware investigates the movement of drones independently of their appearance. In an interesting approach, Mutlu and colleagues explore the use of different flight patterns for drones as indicators of drone personalities and states of affect. By varying the timing of drone flights – altering delays and speed, the spatial aspects of the flights (altitude, directness of path, and tricks like flips and spins) and the quality of the flights (abruptness, smoothness, and wobbles) the researchers created identifiable personalities and states of affect (Mutlu 5-6). Participants reliably identified the personalities of the adventurer, the exhausted drone, and the antisocial drone (Mutlu 6). Participants were also able to identify changes in behavior in the drones, which the team cites as "the first proof that drones' movements themselves can be perceived as portraying an emotional state" (Mutlu 7).

This work suggests that movement is a useful medium for communicating drone intentionality to users and provides evidence that changes in movement quality produce different interpretations of both personality and affect. It also highlights a useful distinction between personality and state of affect. To create a taxonomy of movement qualities that are universally expressive without considering individual movement patterns would be naïve. It is possible that there is a way of interpreting movement qualities beginning from an individualized base of qualities or an individualized range of quantifiable descriptors, effectively normalizing changes in quality so that they account from variations in individual behavior rather than variations in behavior across individuals. As Mutlu's research seems to suggest, this goal may be accomplished through interpreting the base of movement for each person into meaningful information (personality) rather than simply disposing of the data. The study of communicative drone patterns serves as a guiding and validating force for the work of this paper as well as a potential application. Perhaps a better understanding of how quantifiable traits in movement quality affect social interactions will inform the design of communicative flight patterns to create more socially adept drones.

Movement as Indicator of User Intention and State

We have already touched upon the potential to interpret affect and intentionality from movement, but we have not yet explicitly discussed the use of movement to assess the needs and desires of the user of a system beyond predefined, linguistically interpreted gestures. It is clear that movement can be used to deliver subtle cues to human users of technology by varying movement of objects and social characters on screen, varying movements of robots and other animate physical devices, and varying the choreographed gestures by which a user consciously interacts with gesture-based systems. It may also be possible to interpret emotional state and intention of a user from his/her non-conscious movements as humans do in face-to-face conversation. Such an achievement would have applications to creating more satisfying interactions between humans and computers in which both participants in the interaction would read the intentions of the other to inform responses and follow-up prompts. Systems with this capability might be used in assistive technology, education, and customer service interfaces, in which sensitivity to a user’s needs is essential to meeting the goals of the interaction.

We have observed the complexity of the nature of the interpretation of movement in the human brain beyond a visual experience of the movement itself; it accounts for facial expressions, sensory data from other modalities, individualized characteristics of movement, the appearance of the moving body, and contextual information. Beyond that, we have observed a complex web of contextual information that could be considered from immediate spatial context to temporal context like repetition and temporal placement within an interaction to previously established relationships between interaction partners to verbal content. There is even evidence that mirror neurons fire in our own brains when we watch another person move, so we have a similar movement experience in our stationary physical bodies that could be eliciting an emotional response. We are a long distance away from broadly considering these factors in computational analysis of movements, but it seems that consideration of movement quality may be the first step toward building truly responsive, sensitive human-computer interfaces.

Precedents: Laban in Computational Classification of Quality and Affect

Although the work of this paper is useful for any of the previously mentioned applications, we are concerned primarily with movement quality as an indicator of user intention, exploring the insights that the field of dance can offer in the creation of such systems. Specifically, we are investigating the usefulness of the Laban system for movement analysis focusing on the Effort graph for assessing user intentionality in interactive systems. Fortunately, several researchers in the field of human-computer interaction have begun this investigation in the recent years.

In 2001, doctoral student in the cognitive sciences at University of Pennsylvania Liwei Zhao wrote a dissertation on the use of neural networks to identify Laban Efforts using motion capture data and computer vision for video data. Zhao's approach uses low-level features like height and orientation of sternum, wrist angles, elbow swivel angles, and torsion, curvature, velocity and acceleration of body segments to create a back-propagation neural network for each Affinity in the Laban Efforts– Time, Space, and Weight (Zhao 74-87). Each network is trained on human Laban notator classified data to assign each movement a value for Time, a value for Space, and a value for Weight to perform the composite classification of Laban Effort.

This system is able to predict Laban Efforts performed by certified Laban notators with about 90% accuracy, which is slightly higher than the rate of accuracy of classification by human Laban notators and significantly higher than the accuracy of classification by untrained observers (Zhao 104). Time segmentation in this system is handled with a combination of curvature and the zero-points for the second derivative of the motion with success (Zhao 85). This study provides evidence that algorithmic classification of Laban Efforts is possible for interactive systems. It also establishes features and methods that can successfully be used in the engineering of such a system. It does not address larger questions of relevance to the field of HCI despite sharing similar motivations to those of this paper. In this investigation, we will extend Zhao's work to establish the presence of Laban Efforts in expressive movements by non-performers and attempt to connect the Laban Effort system for classifying movement quality to particular states of affect.

Another series of studies has used Laban and dance systems for assessing movement to guide the development of algorithms that detect expressive qualities. In developing the EyesWeb Expressive Gesture Processing Library, Antonio Camurri and collaborators were informed by Laban and dance systems for analyzing movement as they created a set of meta-features for detecting expressive qualities (Camurri 2-3). This initial research guided future work by HCI researchers Ginevra Castellano and collaborators in their attempt to classify affect in expressive movement. In the later study, extracted features include quantity of motion, contraction index of the body, velocity, acceleration, directness index, and fluidity (Castellano 7). Using these features and various machine learning algorithms– 1-Nearest Neighbor, decision trees, and Naïve Bayes, the researchers attempt to classify four states of affect in the valence-arousal space– anger, joy, pleasure, and sadness (Castellano 3). Classification of anger was the most successful, where the others are successful above chance (Castellano 10). It is evident from this research that quantity of motion is useful for distinguishing arousal levels for identifying affect in the valence-arousal space and contraction index is useful for assessing positive or negative valence (Castellano 10). These results are consistent with expectations according to dance knowledge: higher levels of motion indicate greater levels of excitation and open, wide movements indicate more positive emotional state that closed-off, protective movements. That said, Castellano notes that confusion still occurs between positive and negative states of the same arousal and between positive states of different levels of arousal (Castellano 10). Perhaps a closer following of Laban's principles in feature extraction may improve the accuracy of such classifications.

This assertion is tested in a study by Giraud and collaborators, in which Laban principles for movement analysis guided the design of meta-features for algorithmic identification of affect. Giraud's team recorded motion capture data for 20 students in their early 20's performing simple, pre-choreographed exercise routines in four elicited states: "stressed by the observation of an audience (i.e., negative mood), amused by a video and gifts (positive mood), motivated to perform a session challenging a fictitious audience (i.e., aroused mood) and a control condition" (Giraud 16). The researchers used the Laban Effort-Shape framework to extract five computed features: Impulsiveness (Time Effort), Energy

(Weight Effort), Directness (Space Effort), Jerkiness (Flow Effort), and Expansiveness (Shape Qualities) to explore affect in the valence-arousal space (Giraud 6). An important aspect of their approach is the distinction between push effects–internally motivated, spontaneous reactions to stimuli– and pull effects– responses to external factors constrained by social expectations (Giraud 2). They examine both sides of affect elicitation finding that pull effects tended to have higher levels of energy and arousal (Giraud 14). Overall, they found that aroused conditions were marked by higher mean energy, that positive moods were consistently higher in impulsivity, and that negative moods were associated with greater tension (Giraud 16). To explore the usefulness of the computed features in representing Laban qualities, the team compared the levels of each quality described by the statistics to a human encoding of the qualities, finding that energy and expansiveness were better represented than the others and that expert observers analyzed the qualities more consistently than naïve observers (Giraud 15).

Giraud's team has provided a useful precedent in analyzing the relevance of the Laban Effort graph for the purpose of human-computer interaction, specifically for assessing affect computationally from a person's movements. Their findings suggest that the Laban Effort of a movement may be a useful metric in interpreting affect: that the Time and Weight factors may indicate valence and that Flow, Space and Shape may be useful in determining arousal. They also provide evidence that the quality of movements may change as a result of emotional state rather than simply the form of the movements. By using pre-determined, choreographed movement tasks, the team isolated the effects of elicited emotions on quality itself. Specific states of affect were predicted with less accuracy than one would hope for application in assistive technology and more broadly human-computer interaction. This does not mean that the Laban system can conclusively be eliminated as a potential framework for identifying affect. It is possible that limiting the changes in shape of movements has limited expressivity, prohibiting the observation of full effects on movement quality. Perhaps the changes in form and quality are confounded such that limitations on one impose limitations on the other. Perhaps the computational methods for assessing the Laban qualities were too inaccurate to evaluate the Laban system for use in algorithmic assessment of movement quality. Alternatively, it is possible that Laban Efforts are in no way related to emotional expression in movement. It is even possible that the segmentation of time performed by the team altered the results of numerical analysis on the data. There are too many possible breakdowns in the system to make any broad conclusions about the Laban Effort system's relationship to affect. The research advanced in this thesis will be aimed at filling in some of these relational gaps.

Scope of this Investigation

We have observed in the studies regarding anthropomorphic robots and movement that the appearance of a moving body alters perception of the body's movements. Beyond the size and shape of the body, considerable research suggests that perception of race influences communicative movements patterns. In a 1974 study, cognitive science researchers Word and collaborators provide evidence that differences in race induce delays in movement response times in conversation (Word). Recent work by Kenrick and researchers suggests that the perception of the speed of a moving body changes in response to the race of the moving body (Kenrick 1). The work of psychologist Jennifer Eberhardt suggests that it is possible to identify the race of a person based solely on body movement patterns (Eberhardt 16). Similar evidence exists that gender can be predicted from body movements (Saunders

1). Research in this vein brings up two important issues for movement in human-computer interaction.

First, different bodies move differently. As we have briefly touched upon, it would be naïve to think that we could create a set of movement qualities linked to states of affect (along with algorithms for identifying them) that could be universally applied to all moving bodies. Different bodies express themselves differently, and so it is important to work with diverse populations in developing the computational analysis of movement quality. This concept has important implications for all of the outlined applications, but it most dramatically affects the use of movement quality for assessing user affect in human-computer interactions.

Second, interpretation of movement is altered by the perception of the physical appearance of the moving body. This is consistent with our understanding that movement is interpreted in context, including local context and the context of broader social expectations and relationships. Studies of interpretation of affect and quality, especially those involving the human encoding of movements of other humans on video, must consider the possible effects of physical appearance on interpretation. This idea is particularly relevant to the use of movement to communicate information to the user as we have discussed both on and off the screen.

In this investigation, we acknowledge limitations in our consideration of these factors. Although they are important, they are beyond the scope of this initial investigation. Future efforts will be needed to account for these effects.

METHODOLOGY

The goal of this research is to assess the relevance of classification systems from the field of dance for creating bidirectional interpretation and sensitivity in human-computer interaction. Although we have established a litany of concepts in dance that may be applicable to the creation of movement-based interfaces, we will concern ourselves with evaluating the usefulness of the Laban Efforts for interpreting emotional content encoded in a person's movements. We will approach this problem through an iterative series of pilot studies investigating human perception of movement and intention in the context of conversation and expression of affect to investigate the following research questions:

1. Can people without any formal dance/movement training identify the Laban Efforts in another person's movement?
2. Do people naturally move with the Laban Efforts in expressive interactions?
3. Is there a correlative relationship between certain Laban Effort qualities and a mover's emotional state or intention?

We draw inspiration from the precedents established in the fields of the cognitive sciences and human-computer interaction in the design of these pilot studies.

Measures

Guided by the approaches taken by Michotte, Ekman and Freisen, and Mutlu to establish systems for interpreting meaning and intention from movements, we will conduct a series of studies in which participants will encode the movements of others. In each study, a mixture of trained movers and non-experts, males and females of different ages from various geographic and cultural backgrounds, will label each movement of a subject with a Laban Effort and an emotional interpretation (or interpretation of intention). In the first pilot study, movements encoded will be intentional performances of the Laban Efforts by a Laban-trained mover specifically to determine if humans can observe the Effort qualities when we know they are being performed. In the second pilot study, participants will label the movements of individuals in conversation to determine if the qualities are present and/or perceived in human communication. The collected emotional and Effort data will enable us to assess the accuracy with which the average user of a computer (most likely not a dance expert) can classify Laban Efforts in movements to interpret them if used by computers as a medium to communicate information. We are also searching for evidence that the presence of Laban Efforts in a human's movements imbues those movements with interpretable emotional or intentional content. If this is the case, we can establish a relationship between each Effort and its emotional interpretation, which can be used to design gestural interfaces that both interpret and outwardly communicate emotional intention through movement quality. In the latter of the two studies, the users also encode beginning and end times of gestures, the body parts involved in gestures, and the perceived valance and arousal levels of the overall communication sequence.

Because we are attempting to generalize a framework for movement analysis used by experts in the field of dance beyond applications within that field, we are primarily concerned with subjects outside of the dance world. This presents an obstacle of terminology. We want to determine whether or not humans observe and process the Laban Efforts, not whether or not they can learn to, nor whether or not they understand the vocabulary. In the first pilot study, we will ask participants to encode movements with no introduction to the Laban vocabulary. Then, after a brief and vague introduction to the Laban Effort system, participants will re-encode the movements. We will compare results from the two rounds of encoding to determine the potential language barrier obscuring the investigation. We will also ask users to encode both long videos (about 20 seconds, a sequence of movements of a single Effort) and short videos (about 3-5 seconds, a single movement of approximately the same shape performed with one of the eight Efforts). We will compare findings to assess both the capacity to recognize the Effort qualities in general and the capacity to recognize the Effort qualities independent of shapes or contextual clues. We note that a finding that non-experts are not able to consciously identify Laban Efforts does not rule out the potential use of the system for human-computer interaction design entirely, as the processing is still possible at a non-conscious level.

Effort and emotional classification of movements is collected in both pilot studies, but measures of start/end times and body parts involved in a movement are added to the latter pilot study to shed light on the human process of segmenting time and extracting features in interpreting movements, as discussed in the Background section of this paper. The time segmentation data is also required to evaluate Laban Efforts in the context of a full conversation, as they might occur in the context of human-computer interaction. If we are to determine that the Laban system of Efforts is relevant to interpreting user intention or communicating desired, personalized responses, we must observe that people both perceive and demonstrate these qualities in conversation. This requires the use of longer movement sequences, which requires time-based encodings of movements and their properties. Data regarding the overall interpretation of communication sequences attempts to illuminate the processes by which humans determine the relationship between an individual unit of gesture and a series of movement events (recall the work of McLeod to distinguish between top-down and bottom-up models for interpretation).

In the second pilot-study, we also gather participant encoded measurements of valence and arousal– quantities introduced by psychologist Russell as part of the Circumplex model of affect in 1980 (Russell 1). We collect this data to more easily generalize emotional encodings, as many related words are used in emotional descriptions in Pilot 1, but it is difficult to confirm the relationship between these words as it is subjective and dependent upon context. The Circumplex model provides a useful way of quantifying emotional state and has been harnessed in similar research by Giraud and collaborators (discussed in the Precedents section of this paper).

Instruments

In this project, we will work with video clips rather than live motion sequences as researchers including Kendon and McNeill have done in the past. This decision is primarily motivated by the desire to observe the way multiple people analyze the same sequences of movement in search of generalizable rules or at least generalizability of approach. The easiest way to accomplish this goal is to use video clips for viewings by different people at different times. The use of video clips also enables participants to re-watch movements to improve accuracy in analysis such that accuracy is not hindered by errors of memory. Another advantage of using observations of video over live observations is the capacity to obscure facial expressions and/or audio. Each of the videos used in the second pilot study is absent of facial features and voice recordings, so we can conclude that interpretations are based on content communicated by the body only.

This choice to use videos also presents limitations. The use of video clips and the capacity to view them multiple times abstracts the context of the movements from their usual conversational setting. The process of consciously analyzing movements is not the natural process for movement interpretation, so further investigation will be needed to claim that this type of interpretation occurs in real-time during communication between two people. Nevertheless, evidence that this type of movement quality analysis can be done by untrained observers with a reasonable degree of accuracy (even if out of context) supports the hypotheses that humans can interpret movement quality as an indicator of intention and that computers can be programmed to do the same thing.

Additionally, the introduction of a video camera poses the question of the camera's role in the interaction. It is likely that the awareness of being observed impacts the behavior of movers in the videos, and this potential interference is not accounted for in this project. Efforts were made to minimize this effect. The first pilot study does not attempt to observe human communicators in the context of real conversation but rather attempts to establish that humans are capable of recognizing and interpreting the Laban Efforts with some degree of reliability using videos of performed Laban Efforts, so this concern is less relevant. The second pilot study uses videos from the social network site Youtube.com, in which subjects of the videos are completely unaware of the study. The curated video set from Youtube.com includes children of various ages for their freer expressivity, hypothesizing that they will be less self-conscious than adults about their movements and that their expression will be less consciously altered by the presence of a camera. If this hypothesis is not correct, the evidence that the Laban Efforts are a significant part of natural human communication is weakened, but the evidence that humans observe and interpret the Laban Efforts remains strong.

The second pilot study also uses video animations of motion capture data recorded specifically for this research. The choice to use the animations rather than video controls for the influence of the appearance of bodies, which is abstracted out of the video, on interpretation of their movements. The experience of being recorded by a motion capture system– in this case, the OptiTrack system– involves a body suit covered in ping pong ball-like reflectors, infrared cameras placed around the room, and standing in what is known as the “T-Pose” at the beginning of each recording for calibration purposes. Subjects were not informed of the purpose of the research, but the obvious purpose of observing movements cannot be ignored. To mitigate the impact of the environment, subjects were engaged in answering questions about their own chosen topics in order to distract them from the strange context of the conversation. It is impossible to assert that their awareness of the context did not factor into their behavior, but measures were taken to control this effect.

The written survey method for collecting observations on the chosen movement sequences is motivated by the goal of observing consistency in interpretation amongst the general population. In order to draw conclusions about the generalizability of interpretation of movements, we must collect a sizeable sample of data. This is most easily accomplished by harnessing the power of crowdsourcing. In both studies, surveys and video content are distributed through the Internet and responses are collected and analyzed in Microsoft Excel and R. This enables the collection of data from more people in less time. It also requires quantifiable responses in the way that interviews could not as easily accomplish. Moreover, in the written survey method, participants are able to make their observations under less pressure of observation by survey conductors, thus responses are less likely to be influenced by time pressure or a sense of obligation to the researchers.

The first pilot study gives careful consideration to the format of questions used to label movements with Laban Efforts. Potential question formats include multiple-choice (with various numbers of choices), matching, and free-form response. The use of free-form responses is ruled out in order to minimize the fear of attempting a classification in a foreign discipline without any guidance and to limit responses to only the chosen set of qualities. The use of multiple-choice questions with only a few choices has the obvious disadvantage of improving the odds of chance correct answers, but the use of multiple-choice between all eight Efforts poses the challenge of overwhelming participants' working memory. The use of matching, on the other hand, has the disadvantage of enabling the process of elimination as a tactic in selecting responses. In the first study, both limited multiple-choice questions and matching questions are used, enabling the capacity to compare results from the two methods. Observations of results from different survey methods motivated the use of a drop-down menu of all eight choices for Effort labels in the second study.

The second study makes use of a web application, developed to make time-based encoding easier and more accurate for participants. The web application features a tool with which users could create time segments with automatically filled out forms by pressing and holding a key during the play of video clips. Users are able to drag the endpoints of time segments on a visual timeline to improve accuracy of segmentation and then asked to classify each time segment. This tool is designed to make the process of participating in the research less tedious so that more people will be willing to participate and respond to questions thoughtfully. The survey web application saves user data directly to a database, which is queried and cleaned for analysis, avoiding manual data entry and improving scalability. More information regarding the tool is available in Appendix C.

Analysis

In the pilot studies of this project, we are looking for trends in classification of Laban Efforts performed by different people, as well as trends in emotional interpretation. For videos of intentionally performed Laban Efforts, it will be reasonable to calculate the accuracy of classifications to evaluate the usefulness of the Laban Efforts for interpretation of movement. For both emotional interpretations of movements and Laban Effort labels of conversational movements, it will be reasonable to look for common responses, relationships between emotional interpretations and Laban Efforts, and associations between Laban Effort labels.

In the first pilot study, we are hoping to determine whether or not the Efforts can be observed and classified by non-expert observers, so we will calculate simple accuracy metrics – Accuracy = Number of Correct Answers / Number of Possible Correct Answers – for user responses to each Effort video and each Effort category overall (including all videos for that category), as well as for groups of interest. We will calculate accuracies for each individual participant and then take averages over specific groups – Gender, Survey Format, and Movement Training – to compare the groups. We are also interested in consensus between observers and relationships between the different Efforts as they are perceived, so we will look at Mode, Second Mode, and Spread of labels for each Effort video. The Spread is a metric devised to measure variance in the categorical responses:

$$Spread = \frac{\#Samples^2/\#\ Categories}{\sum_{Cat} Categorical\ Total^2}$$

The metric is normalized so that an even distribution of samples amongst the possible categories (maximum Spread) equals one. The minimum Spread case – in which all samples are assigned to one category – is 1/#Categories – so it is larger when the number of possible categories is larger because the data is concentrated in a smaller subspace of the larger possible space.

We are also comparing survey methods and conducting preliminary associations between the Efforts and emotional interpretations in the first pilot. For this, we will perform calculations of the following quantities:

- Percentage of correct responses and spread for each Effort video and category
    - Before vs. After learning Laban terminology
- Quantity and character of similar emotional encodings (most popular, most related)
- Quality of emotional encodings (do labels in the same Effort contradict each other?)
- Per person accuracy of responses and averages over the groups of interest:
    - Male vs. Female
    - Trained vs. Not trained observers
    - Survey Format Multiple-choice vs. Matching

In the second pilot study, we are searching for the presence of the Laban Efforts in emotional expression and conversation. We are also interested in the segmentation of time and the communicative aspects (features) of emotionally expressive movements.

- Average number and spread of segments per video clip
- Most common Effort and dispersion on each segment
- Most common related emotional encodings associated with each Effort
- Quantity of each Effort encoding in overall emotional encodings
- Patterns of Effort encodings and segments in overall emotional encodings over time

STUDIES

Pilot 1

Do humans perceive Laban Efforts in movements?

The first pilot study advanced two initial questions. Do humans reliably perceive Laban Efforts in each other's movements? Do humans reliably interpret emotional intention from movements with a specific Laban Effort? In order to answer these questions, a collection of videos was created, in which a trained dancer performed body movements classified by each of the eight Laban Efforts: Slash, Punch, Dab, Wring, Press, Flick, Float, and Glide. Videos were encoded by participants for Laban Efforts and emotional interpretation To control for the effects of both obscure terminology and the learning curve involved in understanding the classification system, each of the 16 videos was encoded by participants twice – once with no introduction to Laban, and once after a brief definition of each Effort as a combination of a specific value of Time, Space, and Weight. As discussed in the Methodology chapter of this paper, labeling methods for the videos were in question. To investigate the significance of the labeling method, both matching and multiple-choice strategies were employed in two different versions of the questionnaire, each of which was distributed to half of the participants. To allow maximum range of emotional interpretations, subjects were asked to provide free-form responses for emotional labeling of videos. Survey materials can be viewed in Appendix A.

The experience of participating in the study was as follows. First, participants were presented with a series of long videos – each about 30 seconds long – consisting of multiple movements of multiple body parts in each Effort category. Subjects were asked to encode the videos with the appropriate Effort labels either by multiple-choice between three options or

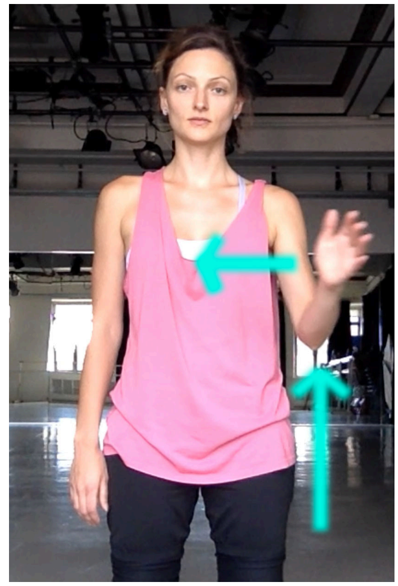

Figure 4: Short Video Gesture

by matching. Second, participants were asked to repeat the encoding task for a series of short videos – only a few seconds long – consisting of a single hand gesture at waist height toward the mid-line of the body (as in Figure 3) performed with each of the eight Efforts. After this, participants were asked to watch a 1:43 video introducing the Laban Affinities of Time, Space, and Weight with demonstrations of the polarities of each. A table identifying each of the eight Efforts as a unique combination of values for each Affinity was presented. Participants were asked to repeat the tasks of encoding both long and short videos after an introduction to the Laban system. Note that an error was made in the survey such that the post-introduction encodings were all completed in free-response form. This is addressed in the Discussion section of this paper. The final section of the study presented three videos, each with a specific emotional intention. Subjects were asked to list Laban Efforts they observed in the videos and provide titles for the videos.

In Table 1 below, the Overall Accuracy was calculated by comparing every Effort label assigned in the study to the correct performed Effort label. The sum of the correct answers was divided by the sum of the answers (excluding missing labels) to find the Overall Accuracy. The average per person accuracy measure was calculated by comparing each participant's Effort label for each

Overall	**Accuracy**	**0.691037736**	
Gender	Female	Male	
	0.68	0.69	
Survey	Matching	Multiple-Choice	
	0.74	0.79	
Training	Trained	Untrained	Laban Trained
	0.69	0.68	0.88
Learning	Pre-Intro	Post-Intro	
	0.71	0.60	

Table 1: Laban Effort Group Results

video to the correct performed Effort. The sum of each individual's correct answers was divided by the sum of that individual's answers to find individual accuracies (included in Appendix B). From there, group averages were calculated for gender groups and movement training background. Accuracies for question format were calculated from the number of correct responses for all questions in each of the two format groups. Accuracies were also calculated including all labels assigned before and after the brief introduction to Laban Movement Analysis. These metrics, along with Mode and second Mode in each category overall are included below in Table 2. Complete metrics for individual videos before and after learning are visible in Appendix B.

All Videos	**Wring**	**Slash**	**Dab**	**Float**	**Punch**	**Flick**	**Press**	**Glide**	
Wring	24	0	0	10	0	0	4	3	*Mode*
Slash	1	39	0	0	2	0	0	0	*Accuracy*
Dab	1	1	29	0	1	2	1	0	*1.0*
Float	17	0	0	34	0	0	0	13	
Punch	0	12	3	0	44	0	0	0	
Flick	0	0	0	0	2	49	0	1	
Press	2	0	17	1	2	0	42	2	
Glide	7	0	2	6	1	1	4	32	
No Resp.	4	4	4	4	4	4	5	5	
Mode	Wring	Slash	Dab	Float	Punch	Flick	Press	Glide	Overall
Accuracy	0.43	0.70	0.53	0.62	0.79	0.88	0.75	0.57	0.65
Spread	0.37	0.21	0.30	0.27	0.18	0.14	0.19	0.28	
Mode 2	Float	Punch	Press	Wring	NR	NR	NR	Float	
Accuracy 2	0.30	0.21	0.31	0.18	0.07	0.07	0.09	0.23	

Table 2: Laban Effort Overall Results

Emotional interpretations of videos are show in Table 3. Here, words are placed in an Effort category according to the performed Effort in the video described rather than the participant's label of the video. The purpose of this is to ensure that the emotional interpretations are connected to their actual movements. Words have been grouped according to similar meanings and counts are reported for the overall group. A table of exact counts for root words used by participants is available in Appendix B.

	Weight: Heavy				Weight: Light			
	Space: Direct		Space: Indirect		Space: Direct		Space: Indirect	
	Press	Count	Wring	Wring	Glide	Count	Float	Count
Time: Sustained	Determined, Fixated, Focused, Serious	6	Cautious, Inhibited, Wary Restricted, Uncomfortable	5	Easeful, Uninhibited Free, Open	5	Confident, Aloof, Regal, Control	6
	Bored, Halfhearted, Dismissive	4	Dull, Malaise, Melancholy, Sad	4	Affectionate, Reassuring, Comfort	3	Relaxed, Peaceful, Tranquil, Calm	5
	Heavy, Push, Resistant, Tension	4	Luxuriant, Reveling, Sensual, Soft	3	Disinterested, Dull, Sad	3	Ease, Free	3
	Assured, Calm, Pleased	3	Annoyed, Irritated	2	Engagement, Alive, Enlightened	3	Compassionate, Soft, Sensual	3
	Disappointed, Overcome	2	Assured, Confident, Strong	2	Calm	2	Light, Whimsical, Dreamy	3
	Reluctant, Uncertain	2	Conniving, Slither	2	Beckoning, Beguiling	2	Loss, Surrender	2
	Searching, Yearning	2	Strain, Tense	2	Conscientious, Reverent	2	Alone	1
	Strong, Control	2	Calm	1	Effort, Resolute	2	Foggy	1
	Restricted, Frustration	2	Changing	1	Swing	1	Tentative	1

	Weight: Heavy				Weight: Light			
	Space: Direct		Space: Indirect		Space: Direct		Space: Indirect	
	Punch	Count	Slash	Count	Dab	Count	Flick	Count
Time: Quick	Angry, Mad	7	Angry, Mad	7	Apathetic, Disinterested, Uncaring, Non-commital, Sarcastic	5	Happy, Playful, Excited	6
	Frustrated, Peeved, Perturbed	5	Frustrated, Annoyed	4	Tentative, Uncertain, Hesitant, Careful, Confusion	5	Whimsical, Soft, Light	3
	Aggressive, Combative, Vengeance	3	Confident, Strong	3	Dull, Melancholy, Passive	3	Annoyed, Irked, On Edge	3
	Controlling	2	Aggressive, Violent, Destroy, Cut	3	Confident, Nonchalant	2	Bouncing, Jumpy	2
	Boom, Slap	2	Hate, Mean, Hostile	3	Calm, Gentle	2	Dismissive, Nonchalant	2
	Firm, Strong	2	Energetic, Effort	2	Punctual, Determined	2	Sarcastic, Smug	2
	Stuck, Tense	2	Retaliatory, Defiant	2	Mad	1	Provoking	1
	Abrupt	1	Satisfied, Resolved	2	Giving	1	Soft	1
	Certainty	1	Fear	1	Stuck	1	Spontaneous	1

Table 4: Emotional Survey Summary

Pilot 2:

How do humans perceive intention in expressive movements?

In the second iteration of the study, participants were asked to encode publicly available videos from the social networking site Youtube.com and animations of motion capture data. The Youtube videos feature children of different races and genders and span the valence-arousal space with expressions of joy, frustration, sadness, and anger. As previously discussed, videos of children were chosen for their freedom of expression and to minimize self-conscious, performative behaviors. Video subjects' faces were obscured by a Gaussian blur to isolate emotional interpretations to those gleaned only from movements. This is a commonly utilized method in the neural sciences to reduce confounding variables in studies of the processing of visually witnessed body movement (Stekelenburg 2, Hadjikhani 1).

Animations of motion capture data were captured from both a male and a female subject. Subjects were recorded in four different elicited states spanning the valence-arousal space: joy, anger, contentment, and sadness. Emotional states were elicited by asking participants for topics that lead them to feel each of the four emotions. Subjects were shown 2 curated videos from Youtube.com focused on the topics selected by them. Then, they were asked a series of questions while being recorded:

1. What happened in each of the videos?
2. Which video was more impactful and why?
3. What about this topic makes you feel this emotion?

Occasionally, subjects were asked more personal follow-up questions in pursuit of the desired emotional state, freeing them from self-judgments that may have prohibited expression in their movements. They were asked to report the valence and arousal of their mood during the interview to verify the elicitation of affect. Documentation of this process is available in Appendix C.

Survey participants were asked to encode three out of twelve possible videos by noting start and end times for movements that they perceived to be expressive, classifying each movement with a Laban Effort and an emotional word, as well as noting involved body parts. For participants, the task of encoding a video with specific times is tedious and time-consuming, so a web application was developed to aid in the process. Screenshots of the application are available in Appendix D.

The volunteers who participated in the study included:

65 people with an average age of 33.4 years,

38 women and 27 men,

31 people with average 16 years of movement training and 34 with none,

and 56 people from the United States and 9 people from other countries.

Due to an indexing error in the application that could not be resolved in production, four out of eight motion capture animations had not been encoded by enough participants to provide reasonable results at the time of submission of this paper. These four videos were eliminated from the analysis process, but the four remaining motion capture videos include a Caucasian female in states of anger and joy and an Asian male in states of sadness and contentment. Thus, each of the four intended states of affect and multiple genders and races are included in the study. After data from these four videos was removed from the set, 556 time segments from eight videos remained. Samples of the cleaned data are available in Appendix E.

In order to assess the accuracy of Effort and affect classifications (when there could have reasonably been none to classify), we need to have agreed upon movements (samples) and a correct label (prediction). Because the problem of time segmentation was left open to participants, we must determine the most commonly identified segments and compare encodings that fall into those segments. We expect the precision of times identified by participants to be somewhat low. To address this issue, K-Means clustering of all segments was used to identify the most likely time segments for each video. Figure 5 presents a cluster plot for 7 segments for Video 1. A combination of human knowledge of the movements in the video and trial and error were used to determine K-Value for K-Means. Table 5 shows start and end times, sum of squares, and size of each of the 41 segment clusters. We can see that clusters range in their within and between sum of squares values, indicating that some clusters are more widely agreed upon than others. For example, Cluster 1 in Video 1 contains 14 segments with a WSS of about 21 and BSS of about 12,000. This indicates a fairly tight clustering of a relatively large number of points in our data set with a large distance between clusters, so we can say with confidence that Cluster 1 represents a set of segments most likely containing the same movement. Cluster 4 in Video 5 on the other hand, contains only 6 points with relatively high WSS of 160. This cluster is more likely to contain segments intended to describe different movements than Cluster 1 in Video 1.

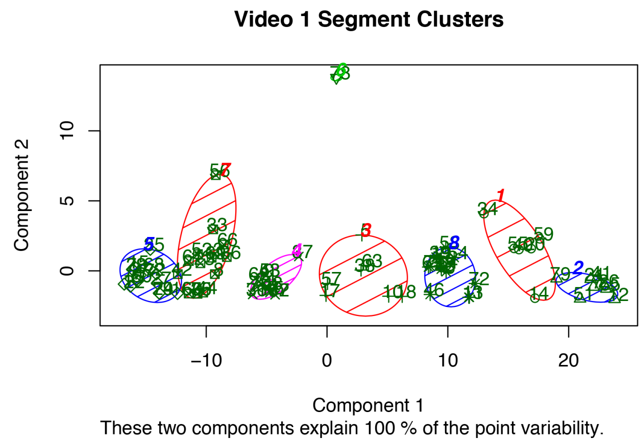

Figure 5: Pilot 2 Clustering

Video	Cluster	Start (s)	End (s)	Total SumSq	Within SS	Between SS	Size
1	1	8.527142857	9.563571429	12384.01068	20.88440714	12108.06988	14
1	2	13.69857143	15.56142857	12384.01068	48.95317143	12108.06988	7
1	3	3.761333333	7.052	12384.01068	86.28941333	12108.06988	15
1	4	1.195	2.744285714	12384.01068	30.33829286	12108.06988	14
1	5	21.42833333	26.32166667	12384.01068	33.46476667	12108.06988	6
1	6	27.53	28.75125	12384.01068	18.4852875	12108.06988	8
1	7	2	24	12384.01068	0	12108.06988	1
1	8	18.24571429	20.83642857	12384.01068	37.52546429	12108.06988	14
2	1	3.978421053	5.983157895	5753.556755	171.6292632	5395.328676	19
2	2	4.21125	21.4875	5753.556755	81.7500375	5395.328676	8
2	3	13.36	16.846	5753.556755	45.91952	5395.328676	5
3	1	5.924545455	9.791818182	6866.774803	62.09983636	6525.520287	11
3	2	0.4	19.82	6866.774803	0	6525.520287	1
3	3	16.7712	18.422	6866.774803	129.251064	6525.520287	25
3	4	0.507272727	2.428636364	6866.774803	73.05629545	6525.520287	22
3	5	9.322	15.438	6866.774803	76.84732	6525.520287	10
4	1	1.67	6.081428571	5996.227576	39.04797143	5859.323195	14
4	2	19.47636364	21.51454545	5996.227576	23.47692727	5859.323195	11
4	3	9.653333333	14.39833333	5996.227576	48.46741667	5859.323195	6
4	4	16.82818182	18.78545455	5996.227576	23.95523636	5859.323195	11
4	5	0.592857143	1.518571429	5996.227576	1.956828571	5859.323195	7
5	1	2.3616	3.9696	19373.64317	283.095632	18373.40324	25
5	2	14.21	17.05615385	19373.64317	162.2255077	18373.40324	13
5	3	25.27275	28.1435	19373.64317	394.5427075	18373.40324	40
5	4	1.305	18.85333333	19373.64317	160.3760833	18373.40324	6
6	1	19.89384615	21.08230769	8581.58336	121.3649385	7516.166204	13
6	2	3.722	6.136	8581.58336	319.1214	7516.166204	25
6	3	25.14875	27.15875	8581.58336	65.447975	7516.166204	8
6	4	12.67894737	15.25578947	8581.58336	559.4828421	7516.166204	19
7	1	31.59230769	34.54692308	23075.74489	38.95090769	22353.27055	13
7	2	17.67666667	21.43238095	23075.74489	184.8430476	22353.27055	21
7	3	25.075	32.155	23075.74489	60.0496	22353.27055	12
7	4	7.309230769	10.46884615	23075.74489	169.65985	22353.27055	26

7	5	16.5	33.5	23075.74489	9	22353.27055	2
7	6	12.551	15.571	23075.74489	126.26176	22353.27055	20
7	7	1.0915	4.308	23075.74489	133.709175	22353.27055	20
8	1	1.702	3.364	9870.188913	8.1684	9392.424006	5
8	2	29.62916667	30.67083333	9870.188913	43.34998333	9392.424006	12
8	3	2.505	16.70857143	9870.188913	174.5085214	9392.424006	14
8	4	19.20444444	28.52444444	9870.188913	139.3806444	9392.424006	9
8	5	15.51916667	17.37666667	9870.188913	112.3573583	9392.424006	12

Table 5: Pilot 2 Cluster Summary

Each of the above clusters was analyzed for both Effort and affect classifications. Clusters containing only one point are excluded from all calculations except the total count of the observations of each Effort. Effort accuracy was calculated taking the mode as the correct Effort label. Agreed Instances for each Effort is a sum of the counts for that Effort when it was either the first or second mode in a cluster. Fraction observed is the fraction of all of the Effort labels for all clusters represented by each Effort. Average Accuracy is the mean of the accuracies for each cluster in which that Effort was the mode. Commonly confused Efforts are included in the table along with a confusion score that measures the degree to which the Efforts are mis/co-classified.

	Slash	Press	Float	Flick	Glide	Dab	Punch	Wring
Agreed Instances	25	20	50	88	60	22	36	10
Total Instances	55	54	87	112	89	50	49	48
Fraction Agreed	0.45	0.37	0.57	0.79	0.67	0.44	0.73	0.21
Fraction Observed	0.10	0.10	0.16	0.21	0.16	0.09	0.09	0.09
Commonly Confused	Flick, Float	Wring, Glide	Flick	Float	Dab	Glide	NA	Flick
Confusion Score	6%	12%	14%	10%	10%	20%	3%	15%
Average Accuracy	0.45	0.52	0.43	0.41	0.41	0.41	0.80	0.43

Table 6: Pilot 2 Effort Summary

	Flick	Dab	Slash	Press	Punch	Float	Wring	Glide
Flick	0.68	0.04	0.04	0.03	0.01	0.10	0.05	0.05
Dab	0.11	0.38	0.04	0.08	0.03	0.10	0.07	0.20
Slash	0.06	0.03	0.71	0.04	0.02	0.06	0.04	0.05
Press	0.08	0.09	0.07	0.41	0.02	0.10	0.12	0.12
Punch	0.02	0.02	0.03	0.02	0.83	0.03	0.03	0.02
Float	0.14	0.06	0.05	0.05	0.02	0.56	0.04	0.09
Wring	0.15	0.08	0.06	0.14	0.03	0.08	0.36	0.09
Glide	0.06	0.10	0.04	0.06	0.01	0.09	0.04	0.60

Table 7: Pilot 2 Effort Confusion

Table 7 provides a complete view of the confusion between each Effort. Confusion scores represent the sum over all of the segments of the product of counts of the two Efforts in question, divided by the difference in counts between them, plus 1 for each segment. This sum is divided by the sum of this quantity over all of the Efforts to show the percentage of co- representation of each Effort pair. This metric provides scores that are higher with larger numbers of co-counts and lower for larger differences between the two counts. For example, if we observed 4 counts of Dab and 1 count of Flick in a single segment, our metric would be lower than if we saw 2 counts of Dab and 3 counts of Flick because the latter situation represents more confusion between the two categories despite having the same co-occuring count. On the other hand, an occurrence of 4 counts of Dab and 0 counts of Flick would result in a 0 confusion statistic for that segment.

An interactive visualization tool was created to help viewers to understand the data. The visualization features the original videos from the survey juxtaposed with all of the timelines of segments submitted by survey participants with start and end times marked. A composite timeline shows start and end times for all segments identified by participants as well as clusters identified by K-Means. A scatter plot of End-time vs. Start-time helps users to visualize the clusters of segments. The user can play the video to see instantaneous Effort modes and accuracies updated in real-time, along with individual participant's Effort labels, emotions, and body parts at each time. Cluster Efforts, accuracies, and spreads are also updated with video play. Average participant-encoded valence and arousal, along with standard deviation of each, are displayed for each video to allow users to better understand the reliability with which participants were able to interpret emotions from the body movements in the videos. Figure 6 is a scaled down screen shot of the visualization. Full-scale screen-shots are available in Appendix E and the interactive application is deployed at http://expressivemovements.com/results.

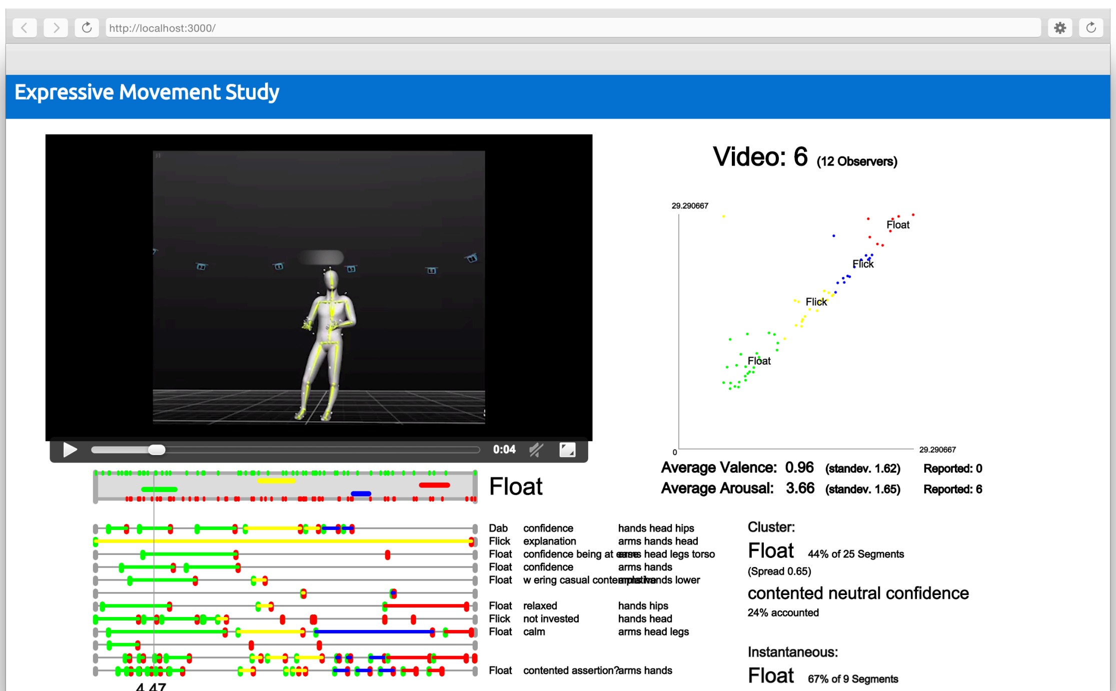

Figure 6: Pilot 2 Visualization

DISCUSSION

Pilot 1

The results from the first study, in which 7 males and 7 females participated, indicate that individuals who are not dance-trained are, indeed, capable of perceiving Laban Efforts in each other's movements with a reasonable amount of accuracy – 65.4%. Initial encodings of the long video clips are impressively accurate at 78.6%. Initial encoding of the short videos is less accurate at 52.2%, which is still greater than chance. There are no noticeable differences in accuracy of classification between males – 69% – and females – 68%. Differences between matching and multiple-choice survey accuracies are minimal with 74% and 79% respectively, indicating that multiple-choice formatting may have been slightly easier for participants to handle. Differences between trained and untrained observers are also minimal with 69% and 68% accuracy respectively, which suggests that these qualitative differences may be observed by both trained and novice movers. However, the Laban-trained participant demonstrates the highest accuracy of 88%, which suggests that Laban training does improve one's ability to accurately perceive Laban Efforts.

Overall accuracy before the introduction is 71% and falls to 60% after the introduction. Values for the Spread statistic tend to be higher for the post-introduction encodings, indicating less agreement between participants. An error was made in the surveys such that the post-learning round of encoding was formatted with free-form labeling of the Efforts in both Survey 1 and Survey 2. This mistake does not factor into the statistics regarding survey question format because they are calculated with only the first round of encoding considered. This weakens conclusions that can be drawn regarding the differences between encodings performed before and after and introduction to Laban, as any differences may be due to the change in question format rather than the introduction. Nevertheless, it is possible that intuitive perception of movement may be more reliable than thoughtful investigation; investigation may present opportunities to overthink and confuse oneself. This conjecture is supported by the theory that interpretation of movement occurs at least partly at the perceptual level of processing. In the second pilot study of this project, all of the Effort labeling is done by selecting an Effort from all eight possible choices to minimize the effects of strategic test-taking on results and because the videos are not composed of intentional performances of pre-planned Effort qualities. Because there is no introduction to the terms in the second pilot study, we will observe the ability of participants to identify movement qualities with some degree of reliability without any form of assistance.

In the data, we can also observe relationships between different Efforts and identify which Efforts might be most universally expressive or identifiable. Short video classifications are probably most comparable to classifications that might occur in the context of a conversation. Punch, Flick, and Press are most consistently identified with 64%, 93%, and 71% accuracy in short videos before the introduction to Laban, so it is likely that they are most universally identified and interpreted. By looking at the second modes for each Effort, we can see that Wring, Float, and Glide seem to be most often confused with each other. Punch and Slash are also often confused, as are Dab and Press. Figure 10 is a graphical visualization of the relationships between the Efforts according to the perception of untrained observers, where the nodes represent Efforts and the edges between them represent mistaken classifications between the Efforts. Edges are darker and wider for more commonly mistaken classifications.

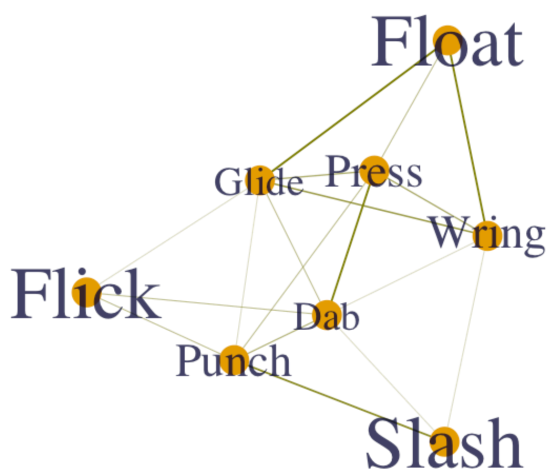

Figure 7: Pilot 1 Effort Results Graph

Regarding emotional interpretation of movements, there are a few qualities that seem to be consistently expressive and a few observable trends over the Efforts. Dab consistently seems to communicate apathy or hesitation. Glide communicates ease. Flick communicates playfulness or lightness. Slash and Punch communicate aggression. More broadly, Sustained movements and Light movements are interpreted generally as less aroused than Quick movements and Heavy movements, which is intuitive as Heavy and Quick movements require more energy. Notice that all of the Sustained movements and most of the Light movements contain the word *calm.* We can also glean that Heavy movements are more likely to be interpreted as negative than Light movements, which is also intuitive. For example, Glide, Float, and Flick contain mostly positive words, where Slash, Punch, and Press contain mostly negative words.

The emotional words in Table 4 were further analyzed for sentiment, keywords, and emotional content. Sentiment was calculated for the full set of emotional words for each Effort using the Natural Language Toolkit Library for Python and the Vader corpus. The average sentiment of each individually analyzed word in each set was also calculated using the same tools. Sentiments reported are scaled up so that they range from -5 to 5 for comparison with human-encoded valences in the second pilot study. The top three keywords and their scores were determined using a publicly available machine learning API called Indico to extract the most relevant words for the set of emotions listed for each Effort. The same API was used to estimate emotional content in each Effort class, assigning a score from 0 to 1 for Anger, Joy, Fear, Sadness, and Surprise.

	Slash	**Punch**	**Wring**	**Press**	**Flick**	**Dab**	**Float**	**Glide**
Top Word	Anger	Anger	Annoyed	Dismissive	Happy	Apathy	Aloof	Calm
Score	0.68	0.68	0.30	0.38	0.68	0.30	0.78	0.68
Word 2	Frustrated	Frustrated	Luxuriant	Calm	Happy	Calm	Ease	Affectionate
Score	0.55	0.55	0.28	0.22	0.58	0.26	0.40	0.24
Word 3	Violent	Combative	Calm	Disappointed	Playful	Disinterested	Relaxation	Beguiling
Score	0.18	0.17	0.26	0.22	0.45	0.24	0.39	0.24
Overall Sentiment	-4.96	-4.95	-4.46	3.35	4.66	-3.06	4.89	4.87
Anger	0.96	0.97	0.11	0.15	0.28	0.63	0.03	0.04
Joy	0.00	0.00	0.04	0.08	0.24	0.01	0.32	0.42
Fear	0.02	0.02	0.46	0.52	0.17	0.28	0.48	0.23
Sadness	0.02	0.01	0.38	0.20	0.11	0.09	0.14	0.08
Surprise	0.00	0.00	0.02	0.05	0.20	0.00	0.02	0.24
Mean Sentiment	-1.17	-1.16	-0.38	0.15	0.51	-0.17	0.83	0.86

Table 8: Pilot 1 Sentiment Analysis

Our initial interpretations of the data for Pilot 1 are supported by this analysis, as we can see that Heavy Efforts tend to have more negative sentiment scores than Light Efforts, and Quick Efforts tend to have more extreme sentiment ratings than their Sustained counterparts.

There are a few obvious limitations to the design of the first pilot study. First, there is only one performer in the videos. It is possible that each performer adds a particular emotional connotation to the performance of each Effort because of personal movement styles and biases. Second, most of the participants are to some degree familiar with the performer and her mode of expression. Participants have experience with the performer as a person, which may have biased their interpretations of expressive movements. Third, this iteration of the study uses video as the medium for analysis, but video data includes facial expressions, even sounds of breathing. The performer in the study tried to keep those fairly neutral, but humans are naturally and non-consciously expressive beings. This concern is addressed in the methods for the second pilot study, in which faces are obscured in all of the videos and motion capture data is animated without any gender/race/body-type identifying characteristics.

Two more conceptual limitations of the first pilot study guided the design of the second pilot study: the handling of time in encoding the videos and the intentional, potentially unnatural performance of Laban Efforts in the videos. As for the former concern, videos of emotional expression are not simply collections of movements that might express a particular emotion. Rather, each video is a narrative in which different parts of the experience of the emotion are conveyed at different times by different movements. In order to assess the relationship between movements with specific Efforts and their emotional interpretation, we must consider how these individual movement building blocks are combined into an expressive movement sequence. This presents the problem of segmentation: how do we divide time to interpret individual movements in the context of the overall narrative and how does each time piece fit together? If we are to do this with a technological system, how do we teach the system to understand the context of the movement or even its beginning and end? Because the time segmentation problem is so significant in interpreting a person's movement in context, as stipulated by both choreographic practice and modern design frameworks, the second pilot study in this thesis considers more carefully the segmentation of time by subjects.

As mentioned above, the first pilot study of this research aims to establish whether or not people perceive Laban Efforts in each other's movements. In order to answer this question, it was necessary that the Laban Efforts exist in the videos shown to participants. The best way to ensure this was to explicitly perform the Efforts in both free-form movements and in short gestures of roughly the same spatial pathways. We observe convincing evidence that humans can accurately perceive Laban Efforts when they are present in movements, but we have not yet established that this is relevant to non-dance, conversational expressive movement. In order to explore this, we need to limit ourselves to the movements of people expressing themselves freely and authentically, which is the focus of the second pilot study in this research.

Pilot 2

The results from the second pilot study support the hypothesis that untrained observers can identify Laban Efforts with greater than chance accuracy in expressive and conversational movements (unintentional performance of Efforts). The average accuracies of all of the Efforts are above 40% (out of eight possible choices), which are well above chance accuracies. As we observed in the first pilot study, certain Efforts appear to be more recognizable than others. Slash, Punch, and Press have average accuracies of 0.45, 0.52, and 0.8. Float, Flick, and Glide have the highest Fraction of Agreement with 0.57, 0.79, and 0.67 respectively. The most commonly observed Effort is Flick, which accounts for 21% of the assigned labels. In this pilot study, we see confusion between Float and Glide, Dab and Flick, Wring and Press, and Slash and Punch.

Again, sentiment and emotion were analyzed for the words provided to describe movements in each cluster using the method described in the discussion of the first pilot study. As you can see in Table 9, Slash and Punch tend to communicate anger, which has a high arousal level and a very negative valence. Press and Wring indicated struggle, as reflected in the significantly negative sentiment ratings for those two Efforts. Flick, Float, and Glide tend to be happy, excited, and wonderment; each has a positive sentiment rating.

	Slash	**Press**	**Float**	**Flick**	**Glide**	**Dab**	**Punch**	**Wring**
Emotion	anger, resignation, rage	defensive, disbelief, resignation, fear	nervous, contented, wonder, neutral, caring, anger	excitement, joy, frustrated, happy, curious	impatient, bored, happy, confused, sad	sad, melow, urgency	anger, resignati on, mad	nervous, neutral, impatience
Overall Sentiment	-4.81	-1.78	0.57	0.76	0.27	-1.61	-3.52	-4.84
Anger	0.81	0.08	0.08	0.39	0.28	0.04	0.79	0.02
Joy	0.01	0.29	0.29	0.21	0.22	0.03	0.05	0.00
Fear	0.13	0.49	0.48	0.26	0.35	0.88	0.07	0.95
Sadness	0.04	0.07	0.09	0.05	0.09	0.04	0.05	0.02
Surprise	0.01	0.07	0.05	0.10	0.06	0.01	0.04	0.00
Average Sentiment	-1.81	-0.18	0.37	0.21	-0.26	-1.32	-1.73	-1.27

Table 9: Pilot 2 Sentiment Analysis

In the latter four videos, which show animations of motion capture data collected for two different participants, we can compare participants' interpretation of emotional valence and arousal to the self-reported values. We can see that participants are generally in the correct quartile of the valence-arousal space, though their estimates for arousal tend to be less extreme than the self-reported values. The standard deviations of around 1.5 for each value indicated that around 68% of the estimates provided by participants fall within 1.5 of the mean value, which is a fairly strong level of agreement amongst parties. This suggests that people can assess emotional interpretation with some degree of accuracy and consistency from only body movements. These physical cues, coupled with facial expressions, contextual clues, and vocal behavior could be strong enough indicators for computers to assess affect quite successfully if the modalities could be well integrated.

	Arousal	Stan. Dev.	Valence	Stan. Dev.	Emotion	Emotion
Subject	10.00		-5.00		Angry	Frustrated
Participants	6.76	1.40	-3.21	1.81	Anger	Frustration
Subject	6.00		0.00		Hope	Content
Participants	3.65	1.65	0.96	1.62	Contented	Nonchalance
Subject	10.00		5.00		Happy	Excited
Participants	4.73	2.48	0.26	1.86	Happy	Impatience
Subject	0.00		-1.50		Depressing	Depressed
Participants	3.44	1.75	-0.99	1.48	Neutral	Boredom

Table 10: Subject Valence and Arousal

In the second pilot study, we observe a much wider spread of the Efforts for each cluster than we saw in the spread of the Efforts for the intentionally performed Efforts. We see mostly lower accuracies. This could be because the Efforts are not as strong or as clearly displayed in conversation. It could be that the Efforts are not the most useful taxonomy for classifying movement quality in conversation between non-dancers. On the other hand, this could be the result of confusion about time segmentation and the survey application.

In this iteration of the study, the openness of the time variable could have led to mislabeled Efforts. Throughout the active survey period, there were instances of poorly loaded videos, incorrectly sized videos (so that timelines did not match up) and trouble with saving data (so that users might have submitted data after a different video had already loaded). Considerable care was taken to ensure that video data was correctly matched with its video or discarded, but there may still be errors leading to contaminated clusters and lower Effort accuracy. It is also possible that too few clusters were defined for some of the videos. The motivation for creating fewer larger clusters is to assess agreement amongst a larger pool of data, but it is possible that different segments within a cluster contain different movements of different Efforts. If clusters are not pure, the decrease in accuracy from the first pilot study to the second may not be the result of an absence of the Efforts in conversational gesturing. Future studies may reduce confusion surrounding time segmentation to draw more firmly grounded conclusions regarding agreement of Effort classification by pre-segmenting timelines for participants. This practice would ensure that participants are referring to the same movements.

Other factors distinguishing the two pilot studies are the format of questions and the presence/absence of an introduction to the Laban terminology. It is possible that unfamiliar vocabulary may have obscured participants' abilities to recognize the movement qualities in question in the second study. It is also possible that the use of multiple-choice and matching formatted questions in the first pilot study artificially augmented participants' abilities to classify Laban Efforts. Future studies should attempt to address these concerns in the context of conversational movement.

In Pilot 2 as in Pilot 1, we are again using videos of a limited number of people moving. We attempt to include people of different racial, gender, and age identities to account for much of the possible group-by-group behavioral differences, but we still only have 6 people included in the videos of this study. It is possible that these particular individuals have their own unique distribution of qualities with which they move that include only some of the Effort qualities. It is also possible that the people in the videos are moving with more exaggerated Effort qualities than the average individual.

In the motion capture videos, specifically, we feature two people in elicited states of affect. Because we asked the subjects for topics related to feelings, they may have been aware of the goal to elicit affect, which may have led to artificial displays of affect or to inaccurate self-reporting of emotional state. If the subjects were in fact not in affected states, perhaps their movements were less expressive than they otherwise might have been. Perhaps, future studies can measure arousal through physical measurements of skin capacitance to verify the emotional state of subjects in hopes of better sketching out the relationship between movement quality and emotional state.

Up to this point, we have not discussed the possibility of augmenting or trimming down Laban's Efforts to create a new taxonomy of movement qualities for the purposes of interpreting intention or designing human-computer interfaces. Throughout the survey process, many participants asked why they could not label a movement with a different quality. Bounce is an example of a quality that is not well accounted for in the Laban Effort System. Nor have we discussed the Laban Spell, Passion, or Vision Drives, which incorporate the Flow Affinity into new qualities. Future studies can experiment with introducing new qualities to the taxonomy and removing those that seem less relevant. This will compromise the structure of the Laban Effort system with its polarities in four Affinities, but perhaps the opening of that space will make way for a new framework for movement quality analysis.

CONCLUSIONS AND FUTURE WORK

In this thesis, we have examined the use of gesture in human-computer interaction from past to present to future. We have established that movement is an essential modality for communication between humans, and we have presented applications for which a better understanding of this modality could be useful in interacting with computers. We have established that current and past movement-based human-computer interfaces rely mostly on shape and spatial referencing, which is in line with the linguistic approach to interpreting body movements as units of language. Moreover, we have observed that current gestural interfaces rely on the same ideas that have prevailed in human-computer interaction since the 1970's and 1980's: direct manipulation and pointers. As the field of gestural interface design struggles to invent new, significant gestures with maximum intuitiveness and minimum fatigue, we propose the inclusion of movement quality in the gestural system design toolkit.

Researchers, especially in the field of dance, have urged the exploration of movement quality as a mechanism for interpreting meaning and intention from physical body movement. Laban's Effort system provides a framework for understanding and classifying movement qualities that could be expressive, and therefore, could be useful as both a medium for input and output in human-computer interaction. The goal of this thesis is to explore the potential use and interpretation of these Efforts for human-computer interaction.

Through a series of two pilot studies, we have investigated the perception of Laban Efforts by the untrained observer in different contexts. We aimed to shed light on several key questions facing the field of qualitative gesture analysis:

1. Can untrained observers identify different movement qualities, in particular the Laban Efforts?

2. Can untrained observers identify the Laban Efforts in conversational movement and do people move with these qualities in communication of emotional experience and intention?

3. Can we establish relationships between the Laban Efforts and different emotional content for use in human-computer interaction and interaction design?

The first pilot study addressed the first and third questions. 14 participants classified videos of intentionally performed Laban qualities with Efforts and emotional interpretations. Participants were able to achieve a 65% rate of accuracy on Effort encodings overall, which is much greater than chance, so we conclude that untrained observers can identify Laban Efforts. Emotional interpretations of each Effort proved to have consistency amongst participants, as well as strong sentiment ratings. It is clear that at the very least, movement quality can play a role in the interpretation of movements for emotion or intention, and that relationships can be drawn between particular qualities and interpretations.

The second pilot study addressed the second and third questions. An application was developed to aid participants in segmenting the time on silent Youtube videos of emotionally affected children (with faces blurred) and motion capture animations of emotionally affected adults. By clustering time segments with the K-Means algorithm, we were able to identify movements consistently picked out by participants. We analyzed Effort and emotional encodings for these segments to find an overall average Effort accuracy (in this case agreement) of 48%, which is not as high as our accuracy in the first study, but is again significantly greater than chance. Again, we found consistency in emotional interpretations of segments and strong sentiment scores. Though these results may have been compromised by issues in data collection, we conclude that untrained observers and movers most likely can perceive and perform the Effort qualities in emotionally expressive movements.

Immediate applications of this research might include new implementations of existing gestural interfaces– like that of the Hololens– that are sensitive to the quality with which gestures are performed. Machine learning algorithms like neural networks and Support Vector Machines can be trained to detect these qualities, and responses elicited from gestural systems can be designed according to the Effort-Affect relationships outlined in this thesis. For example, in a Hololens game that involves shooting space aliens, users could fire larger weapons in response to Slashes than in response to Dabs. In the long term, systems that sense and respond to users' emotions can incorporate a more sophisticated interpretation of body movements as indicators of affect. These systems might include art installations, social robots and virtual characters, and smart homes (including those designed in the assistive technology division). In many of these systems, social characters can be designed to better communicate their emotional states by moving with different qualities in response.

Future studies will attempt to synthesize the two pilot approaches, using pre-segmented video of people engaged in natural expression of emotion to investigate movement quality in the context of conversation and to simplify user experience and data analysis. Larger sample sizes will improve statistical power of future studies, which will be designed with the insights gleaned from this thesis work. The elimination and introduction of new qualities to the taxonomy will explore the possibility of developing an even more powerful framework, informed by the work of Laban and his contemporaries in the field of dance.

Beyond that, it will be necessary to implement gestural systems that detect and react to specific movement qualities as informed by this research on emotional interpretation for user testing. Many choreographers will agree that the design of movements through purely cerebral methods often leads to disembodied experiences. This research is only the first step toward creating a powerful design framework for gestural interfaces that incorporates movement quality and knowledge from the field of dance to achieve more than typical interfaces that rely on pointing, stretching, and swiping.

APPENDIX A: PILOT 1 SURVEY MATERIALS

Date:
Participant name/age:
Gender identification:

Movement Quality Pilot Survey #1

Instructions: Watch each video clip only 1-2 times. Answer questions quickly and instinctually. Do not revise your answer once you have completed a question.

1. Do you have any prior knowledge of Laban Movement Analysis?

2. Have you studied dance or movement in a formal way? If so, for how long?

3. Watch the videos in the *Long Videos* folder. Match the clips to the appropriate movement quality (Efforts) and write any emotional words that come to mind.

Effort	Video	Emotional word	Emotional word
Dab			
Glide			
Press			
Slash			
Wring			
Flick			
Float			
Punch			

4. Watch the videos in the *Short Videos* folder. Match the clips to the appropriate movement quality (Efforts) and write any emotional words that come to mind.

Effort	Video	Emotional word	Emotional word
Dab			
Glide			
Press			
Slash			
Wring			
Flick			
Float			
Punch			

5. Watch the video entitled *Intro To Laban*. Make note of the elements Time, Space, and Weight as they correspond to each of the Efforts outlined in the key below.

Effort	Time	Space	Weight
Dab	*Quick*	*Direct*	*Light*
Glide	*Sustained*	*Direct*	*Light*
Press	*Sustained*	*Direct*	*Heavy*
Slash	*Quick*	*Indirect*	*Heavy*
Wring	*Sustained*	*Indirect*	*Heavy*
Flick	*Quick*	*Indirect*	*Light*
Float	*Sustained*	*Indirect*	*Light*
Punch	*Quick*	*Direct*	*Heavy*

6. Watch the videos in the *Long Videos* folder. Name each clip's Effort from the above list using the information about Time, Space, and Weight.

Video	Time (Quick/Sustained)	Space (Direct/Indirect)	Weight (Heavy/Light)	Effort
A				
B				
C				
D				
E				
F				
G				
H				

7. Watch the videos in the *Short Videos* folder. Name each clip's Effort from the above list using the information about Time, Space, and Weight.

Video	Time (Quick/Sustained)	Space (Direct/Indirect)	Weight (Heavy/Light)	Effort
A				
B				
C				
D				
E				
F				
G				
H				

8. Watch the videos in the *Emotional Videos* folder. Give each video a title and write down any of the above Efforts that you see in each one.

Video	Title	Efforts
A		
B		
C		

Date:
Participant name/age:
Gender identification:

Movement Quality Pilot Survey #2

Instructions: Watch each video clip only 1-2 times. Answer questions quickly and instinctually. Do not revise your answer once you have completed a question.

1. Do you have any prior knowledge of Laban Movement Analysis?

2. Have you studied dance or movement in a formal way? If so, for how long?

3. Watch the videos in the *Long Videos* folder. Choose the Effort that best matches the clip (by highlighting, underlining, or removing others). Write any emotional words that might have been expressed by the mover.

Clip	Effort Options	Emotional word	Emotional word
A	Wring Float Flick		
B	Punch Glide Slash		
C	Float Dab Press		
D	Float Dab Wring		
E	Flick Glide Punch		
F	Flick Glide Slash		
G	Wring Press Slash		
H	Dab Punch Glide		

4. Watch the videos in the *Short Videos* folder. Choose the Effort that best matches the clip, and write emotional words that might have been expressed by the mover.

Clip	Effort Options	Emotional word	Emotional word
A	Wring Dab Press		
B	Punch Glide Slash		
C	Float Wring Press		
D	Float Flick Punch		
E	Flick Glide Punch		
F	Press Glide Slash		
G	Wring Float Slash		
H	Wring Slash Punch		

5. Watch the video entitled *Intro To Laban*. Make note of the elements Time, Space, and Weight as they correspond to each of the Efforts outlined in the key below.

Effort	Time	Space	Weight

Dab	*Quick*	*Direct*	*Light*
Glide	*Sustained*	*Direct*	*Light*
Press	*Sustained*	*Direct*	*Heavy*
Slash	*Quick*	*Indirect*	*Heavy*
Wring	*Sustained*	*Indirect*	*Heavy*
Flick	*Quick*	*Indirect*	*Light*
Float	*Sustained*	*Indirect*	*Light*
Punch	*Quick*	*Direct*	*Heavy*

6. Watch the videos in the *Long Videos* folder. Name each clip's Effort from the above list using the information about Time, Space, and Weight.

Video	Time (Quick/Sustained)	Space (Direct/Indirect)	Weight (Heavy/Light)	Effort
A				
B				
C				
D				
E				
F				
G				
H				

7. Watch the videos in the *Short Videos* folder. Name each clip's Effort from the above list using the information about Time, Space, and Weight.

Video	Time (Quick/Sustained)	Space (Direct/Indirect)	Weight (Heavy/Light)	Effort
A				
B				
C				
D				
E				
F				
G				
H				

8. Watch the videos in the *Emotional Videos* folder. Give each video a title and write down any of the above Efforts that you see in each one.

Video	Title	Efforts
A		
B		
C		

APPENDIX B: PILOT 1 COMPLETE RESULTS

Label	Wring	Wring 2	Slash	Slash 2	Dab	Dab 2	Float	Float 2	Punch	Punch 2	Flick	Flick 2	Press	Press 2	Glide	Glide 2	
Long Videos	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	
Wring	10	9	0	0	0	0	2	4	0	0	0	0	0	0	1	1	
Slash	0	0	13	12	0	0	0	0	0	0	0	0	0	0	0	0	
Dab	0	0	0	1	10	9	0	0	0	0	0	2	0	0	0	0	
Float	2	2	0	0	0	0	11	8	0	0	0	0	0	0	0	4	
Punch	0	0	0	1	0	0	0	0	13	13	0	0	0	0	0	0	
Flick	0	0	0	0	0	1	0	0	0	0	12	12	0	0	0	1	
Press	0	0	0	0	3	4	0	0	0	1	0	0	12	13	0	0	
Glide	1	3	0	0	0	0	0	2	0	0	1	0	0	1	12	7	
Not Answere	1	0	1	0	1	0	1	0	1	0	1	0	2	0	1	1	Mode Accuracy
Mode	Wring	Wring	Slash	Slash	Dab	Dab	Float	Float	Punch	Punch	Flick	Flick	Press	Press	Glide	Glide	1
Accuracy	0.71	0.64	0.93	0.86	0.71	0.64	0.79	0.57	0.93	0.93	0.86	0.86	0.86	0.93	0.86	0.5	Overall Accuracy
Spread	0.23	0.26	0.14	0.17	0.22	0.25	0.19	0.29	0.14	0.14	0.17	0.17	0.17	0.14	0.17	0.36	0.79
Other Signifi	Float	Float			Press	Press	Wring	Wring				Dab	NA			Float	
Accuracy	0.142857	0.142857			0.21	0.29	0.14	0.29				0.14	0.14			0.29	
Short Videos	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	
Wring	3	2	0	0	0	0	2	2	0	0	0	0	2	2	0	1	
Slash	1	0	7	7	0	0	0	0	1	1	0	0	0	0	0	0	
Dab	1	0	0	0	5	5	0	0	1	0	0	0	0	1	0	0	
Float	6	7	0	0	0	0	9	6	0	0	0	0	0	0	4	5	
Punch	0	0	6	5	0	3	0	0	9	9	0	0	0	0	0	0	
Flick	0	0	0	0	0	0	0	0	1	1	13	12	0	0	0	0	
Press	1	1	0	0	7	3	0	1	0	1	0	0	10	7	1	1	
Glide	1	2	0	0	1	1	2	2	1	0	0	0	1	2	8	5	
Not Answere	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	Mode Accuracy
Mode	Float	Float	Slash	Slash	Press	Dab	Float	Float	Punch	Punch	Flick	Flick	Press	Press	Glide	Glide	0.9375
Accuracy	0.21	0.14	0.5	0.5	0.36	0.36	0.64	0.46	0.64	0.64	0.93	0.86	0.71	0.5	0.57	0.36	Overall Accuracy
Spread	0.49	0.4	0.28	0.31	0.32	0.51	0.27	0.46	0.28	0.28	0.14	0.17	0.23	0.4	0.3	0.44	0.52
Other Signifi	Float	Float	Punch	Punch	Press	Press	Glide	Glide		NA		NA	Wring	Wring	Float	Float	
Accuracy	0.43	0.5	0.43	0.36	0.5	0.21	0.14	0.15		0.14		0.14	0.14	0.14	0.29	0.36	
All Videos	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	
Wring	13	11	0	0	0	0	4	6	0	0	0	0	2	2	1	2	
Slash	1	0	20	19	0	0	0	0	1	1	0	0	0	0	0	0	
Dab	1	0	0	1	15	14	0	0	1	0	0	2	0	1	0	0	
Float	8	9	0	0	0	0	20	14	0	0	0	0	0	0	4	9	
Punch	0	0	6	6	0	3	0	0	22	22	0	0	0	0	0	0	
Flick	0	0	0	0	0	1	0	0	1	1	25	24	0	0	0	1	
Press	1	1	0	0	10	7	0	1	0	2	0	0	22	20	1	1	
Glide	2	5	0	0	1	1	2	4	1	0	1	0	1	3	20	12	
Not Answere	2	2	2	2	2	2	2	2	2	2	2	2	3	2	2	3	Mode Accuracy
Mode	Wring	Wring	Slash	Slash	Dab	Dab	Float	Float	Punch	Punch	Flick	Flick	Press	Press	Glide	Glide	1
Accuracy	0.46	0.39	0.71	0.68	0.54	0.5	0.71	0.52	0.79	0.79	0.89	0.86	0.79	0.71	0.71	0.43	Overall Accuracy
Spread	0.2	0.21	0.11	0.12	0.15	0.19	0.12	0.19	0.1	0.1	0.08	0.08	0.1	0.12	0.12	0.2	0.65
Other Signifi	Float	Float	Punch	NA	Press	Press	Glide	Glide	NA	NA	NA	Dab	NA	Glide	Float	Float	
Accuracy	0.29	0.32	0.21	0.07	0.36	0.25	0.07	0.15	0.07	0.07	0.07	0.07	0.11	0.11	0.14	0.32	

Table 10: Pilot 1 Complete Organized Results

Wring	Wring	Slash	Slash	Dab	Dab	Float	Float	Punch	Punch	Flick	Flick	Press	Press	Glide	Glide
Annoyed	1	Anger	6	Apathy	1	Aloof	2	Anger	6	Happy	3	Determinatic	3	Calm	2
Assured	1	Frustrated	3	Calm	1	Confident	2	Frustrated	3	Playful	2	Dismissive	2	Free	2
Calm	1	Strong	2	Careful	1	Ease	2	Controlling	2	Annoyed	1	Assured	1	Affectionate	1
Cautious	1	Aggressive	1	Confident	1	Relaxation	2	Abrupt	1	Bouncing	1	Bored	1	Alive	1
Changing	1	Annoyed	1	Confusion	1	Alone	1	Aggression	1	Dismissive	1	Calm	1	Beckoning	1
Confident	1	Confident	1	Determined	1	Calm	1	Boom	1	Excited	1	Control	1	Beguiling	1
Conniving	1	Cut	1	Disinterestec	1	Compassiona	1	Certainty	1	Irked	1	Disappointec	1	Comfort	1
Dull	1	Defiant	1	Dull	1	Control	1	Combative	1	Jumpy	1	Fixated	1	Conscientiou	1
Inhibited	1	Destroy	1	Gentle	1	Dreamy	1	Firm	1	Light	1	Focused	1	Disinterestec	1
Irritated	1	Effort	1	Giving	1	Foggy	1	Mad	1	Nonchalant	1	Frustration	1	Dull	1
Luxuriant	1	Energetic	1	Hesitant	1	Free	1	Peeved	1	On Edge	1	Halfhearted	1	Easeful	1
Malaise	1	Fear	1	Mad	1	Light	1	Perturbed	1	Provoking	1	Heavy	1	Effort	1
Melancholy	1	Hate	1	Melancholy	1	Loss	1	Slap	1	Sarcastic	1	Overcome	1	Engagement	1
Restricted	1	Hostile	1	Non-commit	1	Peaceful	1	Strong	1	Smug	1	Pleased	1	Enlightened	1
Reveling	1	Mad	1	Nonchalant	1	Regal	1	Stuck	1	Soft	1	Push	1	Open	1
Sad	1	Mean	1	Passive	1	Sensual	1	Tense	1	Spontaneous	1	Reluctant	1	Reassuring	1
Sensual	1	Resolved	1	Punctual	1	Soft	1	Vengeance	1	Whimsical	1	Resistant	1	Resolute	1
Slither	1	Retaliatory	1	Sarcastic	1	Surrender	1					Restricted	1	Reverant	1
Soft	1	Satisfied	1	Stuck	1	Tentative	1					Searching	1	Sad	1
Strain	1	Violent	1	Tentative	1	Tranquil	1					Serious	1	Swing	1
Strong	1			Uncaring	1	Whimsical	1					Strong	1	Uninhibited	1
Tense	1			Uncertainty	1							Tension	1		
Uncomfortak	1											Uncertain	1		
Wary	1											Yearning	1		

Table 12: Pilot 1 Complete Emotional Words List

Age	Years Stu	Years Stu	Gender	Date	Surve	Long Videos																	
						A- Wring				B- Slash				C- Dab				D- Float				E- Punch	
						Pre-learning	Post-learni	Emotional Wc	Emotional V	Pre-learning	Post-learnin	Emotional V	Emotional \	Pre-learnin	Post-lea	Emotiona	Emotiona	Pre-learning	Post-learni	Emotional	Emotional \	Pre-learning	Post-lea
30	20+	20+	F	8/6/16	1	Wring	Wring	Melancholy	Inhibited	Slash	Slash	Defiant	Confident	Dab	Dab	Tentative	Careful	Float	Float	Peaceful	Ease	Punch	Punch
30	0	4	M	9/14/16	1	Wring	Float			Slash	Slash			Press	Press			Float	Float			Punch	Punch
31	0	0	M	9/14/16	1	Float	Wring			Slash	Slash			Dab	Dab			Wring	Wring			Punch	Punch
28			F	9/11/16	2	Wring	Glide			Slash	Slash	Anger	Frustrated	Press	Press	Stuck		Float	Float	Foggy		Punch	Punch
28	0	2	F	9/15/16	2	Wring	Wring	Tense	Restricted	Slash	Slash	Hate	Destroy	Dab	Dab	Hesitant	Gentle	Float	Glide	Light	Soft	Punch	Press
30	0	0	M	9/13/16	2	Wring	Glide			Slash	Slash			Dab	Press			Float	Glide			Punch	Punch
54	0	20+	M	9/13/16	1	Wring	Wring	Luxuriant	Reveling	Slash	Slash	Annoyed	Frustrated	Dab	Dab	Uncertainty		Float	Float	Surrender		Punch	Punch
26	0		M	9/13/16	1	Wring	Wring	Strain	Changing	Slash	Slash	Anger	Hostile	Dab	Dab	Apathy	Non-com	Float	Float	Aloof	Relaxation	Punch	Punch
26	0	0	F	9/13/16	2	Wring	Wring	Slither		Slash	Slash	Strong	Satisfied	Dab	Dab			Float	Wring	Control	Free	Punch	Punch
23	0	0	F	9/13/16	2	Wring	Wring			Slash	Slash			Dab	Dab			Float	Float			Punch	Punch
26	0	0	M	9/13/16	2	Float	Float			Slash	Punch			Press	Press			Wring	Float			Punch	Punch
24	0	0	M	9/14/16	2	Wring	Wring	Malaise		Slash	Slash	Fear		Dab	Dab	Confusion		Float	Float	Loss		Punch	Punch
29	0	14	Queer F	9/15/16	2		Glide	Conniving	Assured		Slash	Effort	Frustrated		Dab	Melanchc	Giving		Wring	Tentative	Dreamy		Punch
27	0	0	F	9/15/16	1	Glide	Wring	Strong	Sensual	Slash	Dab	Aggressive	Energetic	Dab	Flick	Passive	Calm	Float	Wring	Tranquil	Confident	Punch	Punch

Age	Years Stu	Years Stu	Gender	Date	Surve	Long Videos																	
						A- Wring				B- Slash				C- Dab				D- Float				E- Punch	
						Pre-learning	Post-learni	Emotional Wc	Emotional V	Pre-learning	Post-learnin	Emotional V	Emotional \	Pre-learnin	Post-lea	Emotiona	Emotiona	Pre-learning	Post-learni	Emotional	Emotional \	Pre-learning	Post-lea
30	20+	20+	F	42588	1	Wring	Wring	Melancholy	Inhibited	Slash	Slash	Defiant	Confident	Dab	Dab	Tentative	Careful	Float	Float	Peaceful	Ease	Punch	Punch
30	0	4	M	42627	1	Wring	Float			Slash	Slash			Press	Press			Float	Float			Punch	Punch
31	0	0	M	42627	1	Float	Wring			Slash	Slash			Dab	Dab			Wring	Wring			Punch	Punch
28	0	0	F	42624	2	Wring	Glide			Slash	Slash	Anger	Frustrated	Press	Press	Stuck		Float	Float	Foggy		Punch	Punch
28	0	2	F	42628	2	Wring	Wring	Tense	Restricted	Slash	Slash	Hate	Destroy	Dab	Dab	Hesitant	Gentle	Float	Glide	Light	Soft	Punch	Press
30	0	0	M	42626	2	Wring	Glide			Slash	Slash			Dab	Press			Float	Glide			Punch	Punch
54	0	20+	M	42626	1	Wring	Wring	Luxuriant	Reveling	Slash	Slash	Annoyed	Frustrated	Dab	Dab	Uncertainty		Float	Float	Surrender		Punch	Punch
26	0	0	M	42626	1	Wring	Wring	Strain	Changing	Slash	Slash	Anger	Hostile	Dab	Dab	Apathy	Non-com	Float	Float	Aloof	Relaxation	Punch	Punch
26	0	0	F	42626	2	Wring	Wring	Slither		Slash	Slash	Strong	Satisfied	Dab	Dab			Float	Wring	Control	Free	Punch	Punch
23	0	0	F	42626	2	Wring	Wring			Slash	Slash			Dab	Dab			Float	Float			Punch	Punch
26	0	0	M	42626	2	Float	Float			Slash	Punch			Press	Press			Wring	Float			Punch	Punch
24	0	0	M	42627	2	Wring	Wring	Malaise		Slash	Slash	Fear		Dab	Dab	Confusion		Float	Float	Loss		Punch	Punch
29	0	14	Queer F	42628	2		Glide	Conniving	Assured		Slash	Effort	Frustrated		Dab	Melanchc	Giving		Wring	Tentative	Dreamy		Punch
27	0	0	F	42628	1	Glide	Wring	Strong	Sensual	Slash	Dab	Aggressive	Energetic	Dab	Flick	Passive	Calm	Float	Wring	Tranquil	Confident	Punch	Punch

Table 13: Pilot 1 Raw Data

APPENDIX C: PILOT 2 SURVEY DEVELOPMENT

Images from motion capture session 11/9/2016 at NYU MAGNET:

Figure 8: In the Studio

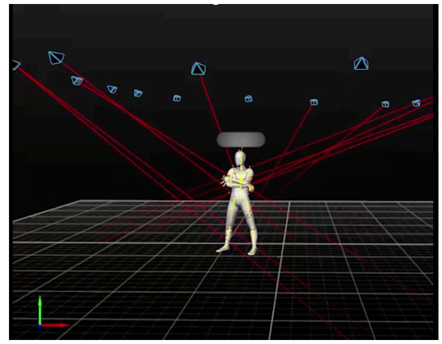

Figure 9: Mocap Rendering

Records on affect elicitation during motion capture session:

	Male Non-Dancer	Arousal	Valence	Emotion	Emotion	Video
Emotion	content	6	0	hope	content	https://www.youtube.com/watch?v=Dha6FzM7afc
Topic	stories					https://www.youtube.com/watch?v=hbmdOzWgyXU
Emotion	joyful	7	2.5	excitement	nostalgia	https://www.youtube.com/watch?v=rKUD4GUWrLU
Topic	games					https://www.youtube.com/watch?v=nyeZ8khSEC0
Emotion	sad	0	-1.5	depressing	depressing	https://www.youtube.com/watch?v=rzmOI7fTALY
Topic	housewor k					https://www.youtube.com/watch?v=GfJiFBqIjPE
Emotion	angry	7	-2.5	angry	depressed	https://www.youtube.com/watch?v=Bf2JfUoXWLU
Topic	tuition					https://www.youtube.com/watch?v=5-IuFSt5xWA
	Female Dancer	Arousal	Valence	Emotion	Emotion	Video
Emotion	content	3	3	calm	serene	https://www.youtube.com/watch?v=9o3cvFFUNWc
Topic	nature					https://www.youtube.com/watch?v=XhHCcH7hyqo
Emotion	joyful	10	5	happy	excited	https://www.youtube.com/watch?v=2J5GzHoKl1Q
Topic	dogs			love	awesome	https://www.youtube.com/watch?v=KBluUZ4NnZg
Emotion	depressin g	2	-3	sad	emotional	https://www.youtube.com/watch?v=qZMX6H6YY1M
Topic	ungrateful children			shitty		https://www.youtube.com/watch?v=958EZG0Tnlg
Emotion	angry	10	-5	frustrated	confused	https://www.youtube.com/watch?v=WhsSzIS84ks
Topic	donald trump			angry	upset	https://www.youtube.com/watch?v=erKZ38iB-Gc

Table 14: Motion Capture Record

APPENDIX D: PILOT 2 SURVEY MATERIALS

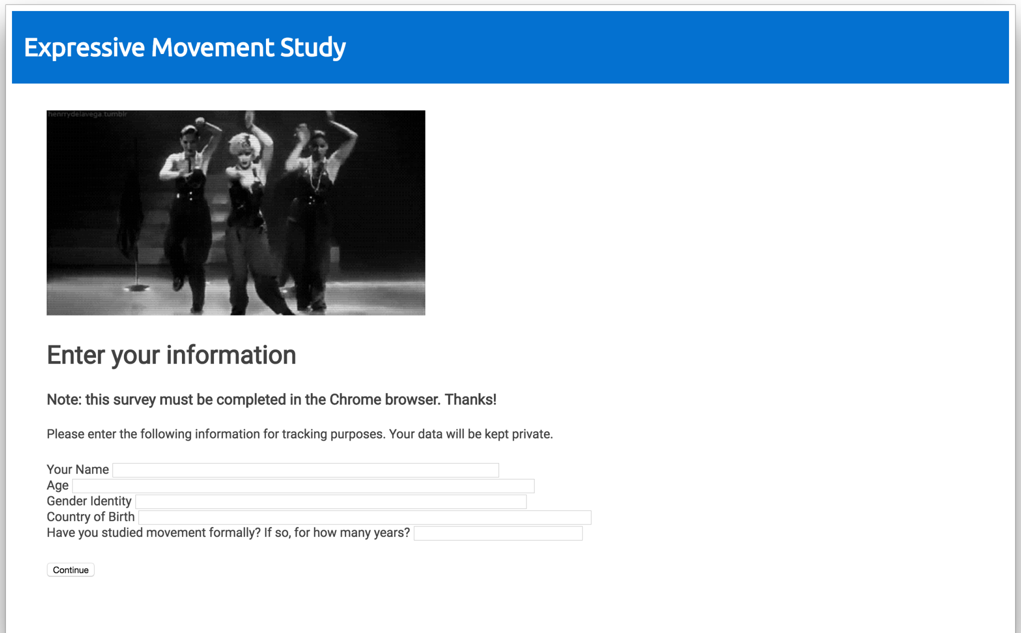

Figure 10: Web Application Home Page

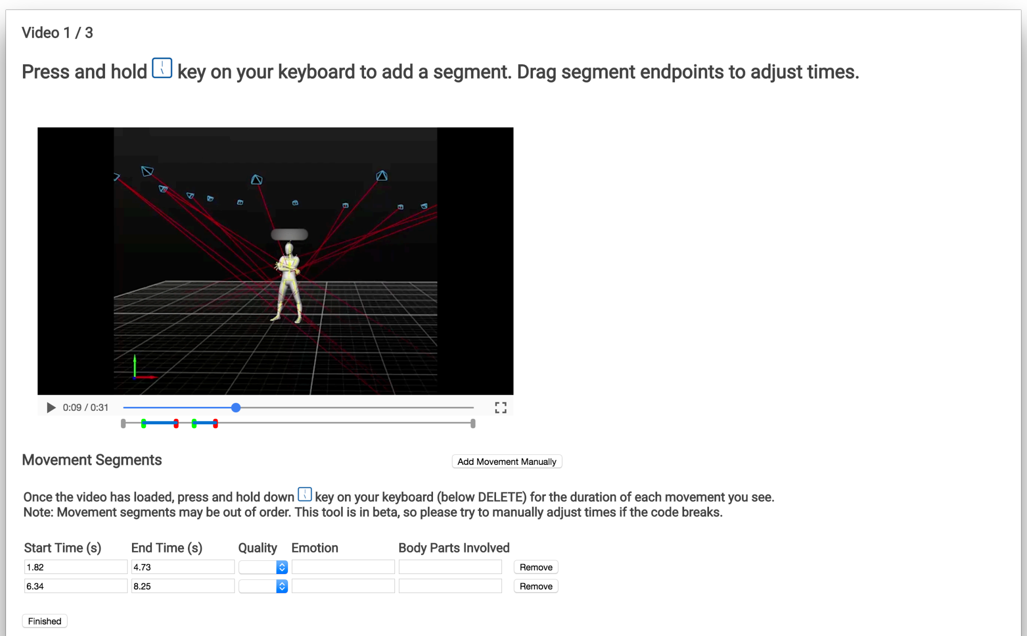

Figure 11: Web Application Survey Page

Code is available at https://github.com/CaitlinSikora/MovementStudies.

APPENDIX E: PILOT 2 SURVEY COMPLETE RESULTS

entry	video	age	gender_	country	moveme	overall	reason	ave_valence	stdev_valenc	valenc	ave_arousal	stdev_arous	arous	segmen	start_time	end_time	laban_effort	emotion	body	cluste
14	1	27	M	USA	5	disbelief and	milder repeated	-2.1012658	2.13394384	-3	5.69620253	1.37145282	4	18	0.27	1.14	Slash	shocked	arms hands	
14	1	27	M	USA	5	disbelief and	milder repeated	-2.1012658	2.13394384	-3	5.69620253	1.37145282	4	19	1.61	3.55	Wring	bewildered	arms hands head	
14	1	27	M	USA	5	disbelief and	milder repeated	-2.1012658	2.13394384	-3	5.69620253	1.37145282	4	20	3.95	7.96	Float	bewildered	hands head hips	
14	1	27	M	USA	5	disbelief and	milder repeated	-2.1012658	2.13394384	-3	5.69620253	1.37145282	4	21	9.03	9.43	Slash	anger	arms hands	
14	1	27	M	USA	5	disbelief and	milder repeated	-2.1012658	2.13394384	-3	5.69620253	1.37145282	4	22	11.51	17.66	Glide	disbelief	feet head hips	
14	1	27	M	USA	5	disbelief and	milder repeated	-2.1012658	2.13394384	-3	5.69620253	1.37145282	4	23	18.26	20.81	Wring	frustrated	arms hands	
14	1	27	M	USA	5	disbelief and	milder repeated	-2.1012658	2.13394384	-3	5.69620253	1.37145282	4	24	27.56	28.77	Press	resignation	hands hips	
34	1	26	M	USA	0	, stubbornness if	i can tell by the v	-2.1012658	2.13394384	-3	5.69620253	1.37145282	6	85	5	7	Glide	wonder	arms hands	
34	1	26	M	USA	0	, stubbornness if	i can tell by the v	-2.1012658	2.13394384	-3	5.69620253	1.37145282	6	86	8	9.94	Flick		arms hands	
34	1	26	M	USA	0	, stubbornness if	i can tell by the v	-2.1012658	2.13394384	-3	5.69620253	1.37145282	6	87	16.19	16.19	Press	itchy	hands	
34	1	26	M	USA	0	, stubbornness if	i can tell by the v	-2.1012658	2.13394384	-3	5.69620253	1.37145282	6	88	20.91	20.91	Flick		hands mouth	
34	1	26	M	USA	0	, stubbornness if	i can tell by the v	-2.1012658	2.13394384	-3	5.69620253	1.37145282	6	89	29.41	29.41	Float	stubborn ste	hands	
42	1	29	M	USA	10	looks like someth	moving hands ex	-2.1012658	2.13394384	-2	5.69620253	1.37145282	5	109	20.88	20.88	Slash	confused	hands	
42	1	29	M	USA	10	looks like someth	moving hands ex	-2.1012658	2.13394384	-2	5.69620253	1.37145282	5	110	24.75	24.75	Float	dissapointed	hands	
58	1	29	F	USA	26	and helplessness	they seem to hav	-2.1012658	2.13394384	-3	5.69620253	1.37145282	5	162	0	2.61	Wring	anxiety	arms hands	
58	1	29	F	USA	26	and helplessness	they seem to hav	-2.1012658	2.13394384	-3	5.69620253	1.37145282	5	163	3.83	3.83	Float	beseechmen	arms hands head	
58	1	29	F	USA	26	and helplessness	they seem to hav	-2.1012658	2.13394384	-3	5.69620253	1.37145282	5	164	12.52	12.52	Flick		arms hands	
58	1	29	F	USA	26	and helplessness	they seem to hav	-2.1012658	2.13394384	-3	5.69620253	1.37145282	5	165	16.98	16.98	Press	bewildermer	arms butt hands	
58	1	29	F	USA	26	and helplessness	they seem to hav	-2.1012658	2.13394384	-3	5.69620253	1.37145282	5	166	17	21	Wring	anxiety	arms hands	
58	1	29	F	USA	26	and helplessness	they seem to hav	-2.1012658	2.13394384	-3	5.69620253	1.37145282	5	167	22	27	Glide	despair	arms hands	
58	1	29	F	USA	26	and helplessness	they seem to hav	-2.1012658	2.13394384	-3	5.69620253	1.37145282	5	168	27	29	Press	defiance	arms hands	
61	1	29	F	USA	26	persuasion,	he moves a lot a	-2.1012658	2.13394384	-2	5.69620253	1.37145282	5	176	0.74	1.4	Punch	frustrated	arms hands	
61	1	29	F	USA	26	persuasion,	he moves a lot a	-2.1012658	2.13394384	-2	5.69620253	1.37145282	5	177	3.61	6.69	Float	whimsical	hips legs torso	
61	1	29	F	USA	26	persuasion,	he moves a lot a	-2.1012658	2.13394384	-2	5.69620253	1.37145282	5	178	8.23	9.29	Slash	fed up	arms hands	
61	1	29	F	USA	26	persuasion,	he moves a lot a	-2.1012658	2.13394384	-2	5.69620253	1.37145282	5	179	17.85	20.65	Punch	frustrated	arms hands head	
61	1	29	F	USA	26	persuasion,	he moves a lot a	-2.1012658	2.13394384	-2	5.69620253	1.37145282	5	180	28.17	29.5	Dab	confident	arms hands torso	
61	1	29	F	USA	26	persuasion,	he moves a lot a	-2.1012658	2.13394384	-2	5.69620253	1.37145282	5	181	2.13	3.14	Flick	beckoning	arms hands	
76	1	55	F	USA	0	curious/question	quick movement	-2.1012658	2.13394384	3	5.69620253	1.37145282	7	262	0	2.36	Flick	curious ques	hands	
76	1	55	F	USA	0	curious/question	quick movement	-2.1012658	2.13394384	3	5.69620253	1.37145282	7	263	2.76	2.76	Press	excitement	hands	
76	1	55	F	USA	0	curious/question	quick movement	-2.1012658	2.13394384	3	5.69620253	1.37145282	7	264	5	5	Slash	anger	hands	
76	1	55	F	USA	0	curious/question	quick movement	-2.1012658	2.13394384	3	5.69620253	1.37145282	7	265	8.23	8.23	Flick		hands	
76	1	55	F	USA	0	curious/question	quick movement	-2.1012658	2.13394384	3	5.69620253	1.37145282	7	266	9.54	9.54	Glide	resignation	feet hands	
100	1	29	M	USA	1	with the fact tha	he seems to be l	-2.1012658	2.13394384	-2	5.69620253	1.37145282	6	360	2.62	9.14	Wring	speaking	arms head torso	
100	1	29	M	USA	1	with the fact tha	he seems to be l	-2.1012658	2.13394384	-2	5.69620253	1.37145282	6	361	17.48	25.95	Wring	confusion	arms head	
109	1	30	F	USA	25	pleading, resistar	repetition of ges	-2.1012658	2.13394384	-3	5.69620253	1.37145282	7	384	0	4.42	Dab	pleading	hands	
109	1	30	F	USA	25	pleading, resistar	repetition of ges	-2.1012658	2.13394384	-3	5.69620253	1.37145282	7	385	4.82	8.56	Float	questioning	arms hands head	
109	1	30	F	USA	25	pleading, resistar	repetition of ges	-2.1012658	2.13394384	-3	5.69620253	1.37145282	7	386	8.96	12.85	Punch	agression	arms hands	
109	1	30	F	USA	25	pleading, resistar	repetition of ges	-2.1012658	2.13394384	-3	5.69620253	1.37145282	7	387	13.25	15.86	Wring	distracted	fingers hip	
109	1	30	F	USA	25	pleading, resistar	repetition of ges	-2.1012658	2.13394384	-3	5.69620253	1.37145282	7	388	16.93	20.94	Dab	pleading	hands	

Table 15: Sample of Pilot 2 Data

video	cluster	start_time	end_time	totss	withinss	betweenss	size	spread	mode	accuracy	emotion	flick	dab	slash	press	punch	float	wring	glide	emo_rate	words	top_word1
1	1	8.52714286	9.56357143	12384.0107	20.8844071	12108.0699	14	0.67586207	Slash	0.42857143	anger resignatio	4	NA	6	NA	1	1	NA	2	0.22222222	anger resigna	anger
1	2	13.6985714	15.5614286	12384.0107	48.9531714	12108.0699	7	0.75384615	Press	0.42857143	anxious bewilde	1	1	NA	3	NA	NA	1	1	0.16666667	disbelief itch	bewildermer
1	3	3.76133333	7.052	12384.0107	86.2894133	12108.0699	15	0.42056075	Float	0.66666667	anger confusion	1	NA	2	NA	NA	10	1	1	0.13333333	bewildered v	anger
1	4	1.195	2.74428571	12384.0107	30.3382929	12108.0699	14	0.7	Flick	0.35714286	curious exciteme	5	2	1	2	1	1	2	NA	0.15384615	shocked bew	excitement
1	5	21.4283333	26.3216667	12384.0107	33.4647667	12108.0699	6	0.75	Glide	0.5	abandonment a	NA	NA	NA	NA	1	1	1	3	0.16666667	dissapointed	confusion
1	6	27.53	28.75125	12384.0107	18.4852875	12108.0699	8	0.64	Press	0.5	anger anxious cc	NA	1	1	4	NA	1	NA	1	0.125	resignation s	stubborn
1	7	2	24	12384.0107	0	12108.0699	1	1	Flick	1	confusion	1	NA	NA	NA	NA	NA	NA	NA	1	confusion	confusion
1	8	18.2457143	20.8364286	12384.0107	37.5254643	12108.0699	14	0.74242424	Flick	0.28571429	frustrated impat	4	1	3	NA	1	1	4	NA	0.27272727	frustrated co	frustrated
2	1	3.97842105	5.9831579	5753.55676	171.629263	5395.32868	19	0.57301587	Dab	0.36842105	sad melow cont	NA	7	1	2	1	NA	1	7	0.44444444	not melow m	melow
2	2	4.21125	21.4875	5753.55676	81.7500375	5395.32868	8	0.91428571	Glide	0.25	sad determined	NA	1	2	2	NA	NA	1	2	0.625	not determir	patience
2	3	13.36	16.846	5753.55676	45.91952	5395.32868	5	0.75757576	Dab	0.6	sad urgency	NA	3	NA	NA	NA	NA	1	1	0.8	sad sad urge	sad sad
3	1	5.92454546	9.79181818	6866.7748	62.0998364	6525.52029	11	0.97580645	Float	0.27272727	caring excitemer	NA	2	NA	3	NA	3	NA	3	0.18181818	desire love a	excitement
3	2	0.4	19.82	6866.7748	0	6525.52029	1	1	Flick	1	excitement	1	NA	NA	NA	NA	NA	NA	NA	1	excitement	excitement
3	3	16.7712	18.422	6866.7748	129.251064	6525.52029	25	0.75030012	Flick	0.32	excitement excit	8	3	2	2	NA	5	3	2	0.4	joy exciteme	excitement
3	4	0.50727273	2.42863636	6866.7748	73.0562955	6525.52029	22	0.55632184	Glide	0.54545455	excitement hap	4	NA	NA	1	NA	3	2	12	0.36363636	surprise curi	excitement
3	5	9.322	15.438	6866.7748	76.84732	6525.52029	10	0.83333333	Float	0.3	caring acknowle	NA	2	NA	1	1	3	NA	3	0.3	disbelief cari	caring
4	1	1.67	6.08142857	5996.22758	39.0479714	5859.3232	14	0.57647059	Punch	0.92857143	anger angry den	NA	NA	NA	NA	13	NA	1	NA	0.58333333	anger mad a	anger
4	2	19.4763636	21.5145455	5996.22758	23.4769273	5859.3232	11	0.48594378	Punch	0.81818182	anger angry resi	NA	NA	NA	NA	9	NA	1	1	0.44444444	frustrated ar	anger
4	3	9.65333333	14.3983333	5996.22758	48.4674167	5859.3232	6	0.66666667	Press	0.66666667	determination p	NA	NA	NA	4	1	NA	NA	1	0.5	determinatic	determinatic
4	4	16.8281818	18.7854546	5996.22758	23.9552364	5859.3232	11	0.58454106	Punch	0.72727273	anger angry mac	NA	NA	2	NA	8	NA	1	NA	0.6	mad anger a	anger
4	5	0.59285714	1.51857143	5996.22758	1.95682857	5859.3232	7	0.66216216	Punch	0.85714286	anger angry den	NA	NA	NA	NA	6	NA	1	NA	0.42857143	anger mad a	anger
5	1	2.3616	3.9696	19373.6432	283.095632	18373.4032	25	0.6684492	Flick	0.48	annoyed interes	12	3	NA	3	NA	3	NA	4	0.08695652	withdrawal h	thoughtful
5	2	14.21	17.0561539	19373.6432	162.225508	18373.4032	13	0.79716981	Flick	0.46153846	anger thoughtfu	6	3	NA	2	NA	NA	2	NA	0.15384615	hurt irritated	anger
5	3	25.27275	28.1435	19373.6432	394.542708	18373.4032	40	0.49689441	Slash	0.475	anger angry frus	4	1	19	7	2	2	5	NA	0.33333333	pain anger p	angry
5	4	1.305	18.8533333	19373.6432	160.376083	18373.4032	6	0.85714286	Press	0.5	defensive disagr	NA	NA	2	3	NA	1	NA	NA	0.33333333	fear disagree	fear
6	1	19.8938462	21.0823077	8581.58336	121.364939	7516.1662	13	0.63773585	Flick	0.38461539	contented neutr	5	1	NA	NA	NA	5	1	1	0.23076923	relaxed happ	neutral
6	2	3.722	6.136	8581.58336	319.1214	7516.1662	25	0.65445026	Float	0.44	contented neutr	7	2	NA	NA	NA	11	1	4	0.24	concerned cc	neutral
6	3	25.14875	27.15875	8581.58336	65.447975	7516.1662	8	0.88888889	Float	0.375	neutral contente	1	NA	2	NA	NA	3	NA	2	0.375	relaxed expla	neutral
6	4	12.6789474	15.2557895	8581.58336	559.482842	7516.1662	19	0.82988506	Flick	0.31578947	contented neutr	6	1	4	NA	NA	5	NA	3	0.15789474	confidence e	neutral
7	1	31.5923077	34.5469231	23075.7449	38.9509077	22353.2706	13	0.80476191	Glide	0.30769231	bored happy agr	2	1	2	1	NA	3	NA	4	0.15384615	contemplati	bored
7	2	17.6766667	21.432381	23075.7449	184.843048	22353.2706	21	0.51219512	Glide	0.47619048	happy impatient	2	1	1	2	NA	3	2	10	0.1	happy neutra	impatient
7	3	25.075	32.155	23075.7449	60.0496	22353.2706	12	0.51428571	Flick	0.66666667	anxious curious	8	NA	NA	1	1	2	NA	NA	0.16666667	contemplati	anxious
7	4	7.30923077	10.4688462	23075.7449	169.65985	22353.2706	26	0.528125	Flick	0.42307692	happy bored rel	11	4	2	1	3	2	1	2	0.23076923	contentment	bored
7	5	16.5	33.5	23075.7449	9	22353.2706	2	1	Glide	0.5	anxiety deep	NA	NA	NA	NA	NA	NA	1	1	0.5	deep anxiety	anxiety
7	6	12.551	15.571	23075.7449	126.26176	22353.2706	20	0.5952381	Glide	0.45	happy annoyed	4	3	NA	1	NA	2	1	9	0.3	boring happ	tired
7	7	1.0915	4.308	23075.7449	133.709175	22353.2706	20	0.64102564	Flick	0.4	happy relaxed al	8	5	2	1	NA	3	NA	1	0.1	relaxing disa	relaxed
8	1	1.702	3.364	9870.18891	8.1684	9392.42401	5	0.75757576	Float	0.6	concentrated cu	1	NA	NA	NA	NA	3	1	NA	0.2	nervous curi	nervous
8	2	29.6291667	30.6708333	9870.18891	43.3499833	9392.42401	12	0.75789474	Float	0.41666667	neutral bored cu	1	NA	NA	2	NA	5	2	2	0.18181818	nervous neu	nervous
8	3	2.505	16.7085714	9870.18891	174.508521	9392.42401	14	0.62820513	Wring	0.42857143	impatience nerv	2	1	NA	3	NA	1	6	1	0.14285714	nervous atte	nervous

Table 13: Pilot 2 Cluster Data

mode	accuracy	words	top_word	score	top_word	score2	top_word	score3	total_sent	anger	joy	fear	sadness	surprise	ave_senti
Slash	0.42857143	anger resign	anger	0.61769525	dismissive	0.27719926	resignation	0.44445604	-4.63	0.63424742	0.02569621	0.24905682	0.0759837	0.01501586	-1.3344375
Press	0.42857143	disbelief itch	bewildermer	0.27094926	itchy	0.27094926	disbelief	0.38969668	-3.8585	0.11273852	0.06759818	0.71090388	0.07341064	0.03534879	-0.966
Float	0.66666667	bewildered v	anger	0.52761281	confusion	0.52939853	wonder	0.48207761	-4.2595	0.04702497	0.01128521	0.90939665	0.02334841	0.00894484	-0.4554
Flick	0.35714286	shocked bew	excitement	0.61511281	curious	0.51689853	frustrated	0.62939853	-1.909	0.26769722	0.04101599	0.57169449	0.08457494	0.0350173	-0.1333846
Glide	0.5	dissapointed	confusion	0.27719926	dissapointed	0.38969668	agitation	0.22719926	-4.18	0.13078111	0.20557816	0.2828159	0.27945292	0.10137196	-1.1590833
Press	0.5	resignation s	stubborn	0.2960258	resignation	0.33969668	defiance	0.27094926	-2.6335	0.01972023	0.03510106	0.91643721	0.01665044	0.01209105	-0.331125
Flick	0.28571429	frustrated co	frustrated	0.61769525	impatience	0.44189853	pleading	0.28782258	-4.858	0.68841493	0.00724408	0.2618621	0.04098702	0.0014919	-1.6335455
Dab	0.36842105	not melow m	melow	0.64377573	sad	0.40868475	sad	0.51689853	-4.6345	0.01126131	0.00964495	0.96635723	0.01005578	0.00268075	-0.7693333
Glide	0.25	not determir	patience	0.22719926	sad	0.31535141	sad	0.51689853	4.3345	0.05013816	0.03730666	0.83520567	0.05915978	0.01818971	-1.2771875
Dab	0.6	sad sad urge	sad sad	0.52172242	urgency	0.22094926	sad	0.71769525	-4.5405	0.05385307	0.02820784	0.83934021	0.06322572	0.01537315	-1.9068
Float	0.27272727	desire love a	excitement	0.52761281	caring	0.43705159	tenderness	0.27094926	4.9015	0.01061243	0.82619941	0.03100348	0.01612661	0.11605804	1.94581818
Flick	0.32	joy exciteme	excitement	0.51615415	joy	0.67939336	happy	0.47103162	4.9815	0.00047104	0.582955	0.05705297	0.00527329	0.35424772	1.99642
Glide	0.54545455	surprise curi	excitement	0.44445604	surprise	0.42985531	happy	0.52761281	4.9785	0.00010086	0.9053309	0.0008149	0.00047472	0.09327865	2.08975
Float	0.3	disbelief cari	caring	0.44445604	engaging	0.43705159	disbelief	0.38969668	4.8855	0.00620239	0.8750236	0.02375859	0.01191533	0.08310007	1.9686
Punch	0.92857143	anger mad a	anger	0.66082193	angry	0.45439853	mad	0.27188786	-4.9375	0.97196662	0.00121485	0.02070656	0.00553544	0.00057647	-2.1576667
Punch	0.81818182	frustrated ar	anger	0.43035348	angry	0.45439853	resignation	0.54011281	-4.9105	0.93553686	0.00801292	0.03285064	0.01842807	0.0051715	-2.4597222
Press	0.66666667	determinatic	determinatic	0.16663246	proving	0.19155765			2.0095	0.19362044	0.22325394	0.22955558	0.17068422	0.18288581	1.00475
Punch	0.72727273	mad anger a	anger	0.44445604	angry	0.45439853	mad	0.33969668	-4.9425	0.95659256	0.00496861	0.0227945	0.01239337	0.00325096	-2.72855
Punch	0.85714286	anger mad a	anger	0.61769525	angry	0.45439853	mad	0.22719926	-4.839	0.89684665	0.0134904	0.05143424	0.02885658	0.00937211	-2.3077143
Flick	0.48	withdrawal h	thoughtful	0.2670008	annoyed	0.54189853	sass	0.44189853	-4.7545	0.97062624	0.00051641	0.02011147	0.00862946	0.00011638	-0.5852609
Flick	0.46153846	hurt irritated	anger	0.45439853	thoughtful	0.47774867	hurt	0.29577671	-4.7465	0.91024381	0.00765002	0.06685798	0.01312006	0.00212812	-0.9871154
Slash	0.475	pain anger p	angry	0.55439853	frustration	0.43035348	rage	0.49781733	-4.9935	0.99275875	8.18E-05	0.00556786	0.00157915	1.23E-05	-2.2918472
Press	0.5	fear disagree	fear	0.33969668	disagreemen	0.22719926	defensive	0.52564516	-2.6335	0.01013425	0.832618	0.08569537	0.01379842	0.05775394	-0.4419167
Flick	0.38461539	relaxed happ	neutral	0.45439853	contented	0.41224839	agitation	0.27719926	4.7465	0.11838026	0.40297401	0.13832314	0.09269016	0.24763237	1.02484615
Float	0.44	concerned cc	neutral	0.45439853	careless	0.54189853	contented	0.46882959	4.9345	0.1807595	0.29056811	0.26440311	0.11406528	0.150204	0.83294
Float	0.375	relaxed expl	neutral	0.55439853	resignation	0.27719926	contented	0.46882959	3.5015	0.28763419	0.22731736	0.25942594	0.18714291	0.03847952	0.5486875
Flick	0.31578947	confidence e	neutral	0.45439853	contented	0.41224839	relax	0.35166667	4.7225	0.74259472	0.11669543	0.08998845	0.02148158	0.02923981	0.45060526
Glide	0.30769231	contemplativ	bored	0.44189853	contemplativ	0.31060577	happy	0.44189853	4.4895	0.0765596	0.41116756	0.40873736	0.01636104	0.0871744	0.61688462
Glide	0.47619048	happy neutra	impatient	0.51689853	curious	0.26450636	happy	0.67939336	-4.43	0.35901642	0.01874324	0.53565526	0.07816945	0.0084156	-0.480575
Flick	0.66666667	contemplativ	anxious	0.54189853	curious	0.61689853	bored	0.32188786	-0.258	0.00103385	0.011476	0.983239	0.00151788	0.00273332	-0.065125
Flick	0.42307692	contentment	bored	0.44189853	contemplativ	0.23320633	happy	0.44445604	4.9685	0.00394499	0.71421588	0.07242799	0.0675832	0.14182797	1.42980769
Glide	0.5	deep anxiety	anxiety	0.22094926	deep	0.33969668			-0.8895	0.14788753	0.15343219	0.43876284	0.12304992	0.13686754	-0.44475
Glide	0.45	boring happy	tired	0.45439853	annoyed	0.51689853	happy happy	0.51765514	2.7115	0.86267221	0.0373963	0.07012715	0.00209396	0.02771034	0.02385
Flick	0.4	relaxing disa	relaxed	0.47713564	confused	0.45439853	happy	0.44189853	4.7015	0.23171786	0.1871945	0.29556102	0.11892597	0.16660067	0.572175
Float	0.6	nervous curi	nervous	0.38969668	pensive	0.22094926	curious	0.27094926	-0.64	0.01406397	0.02719961	0.93324947	0.01513961	0.01034735	-0.1278
Float	0.41666667	nervous neu	nervous	0.38969668	neutral	0.44445604	disagreemen	0.27719926	-4.3895	0.09049887	0.01434186	0.54538006	0.34027126	0.00950796	-0.7692273
Wring	0.42857143	nervous atte	nervous	0.76082193	neutral	0.44189853	impatience	0.44189853	-4.841	0.01763137	0.00327791	0.95444006	0.02426553	0.00038507	-1.2717857
Float	0.33333333	nervous ann	nervous	0.71769525	obstinence	0.27094926	annoyance	0.2960258	-4.4035	0.02294073	0.01397586	0.9098829	0.04862798	0.00457253	-0.9572778
Glide	0.25	questioning l	anger	0.27719926	bored	0.58207761	confused	0.52761281	-4.8285	0.58678585	0.0067999	0.24323344	0.16169353	0.00148728	-1.4160833

Table 14: Pilot 2 Emotional Data

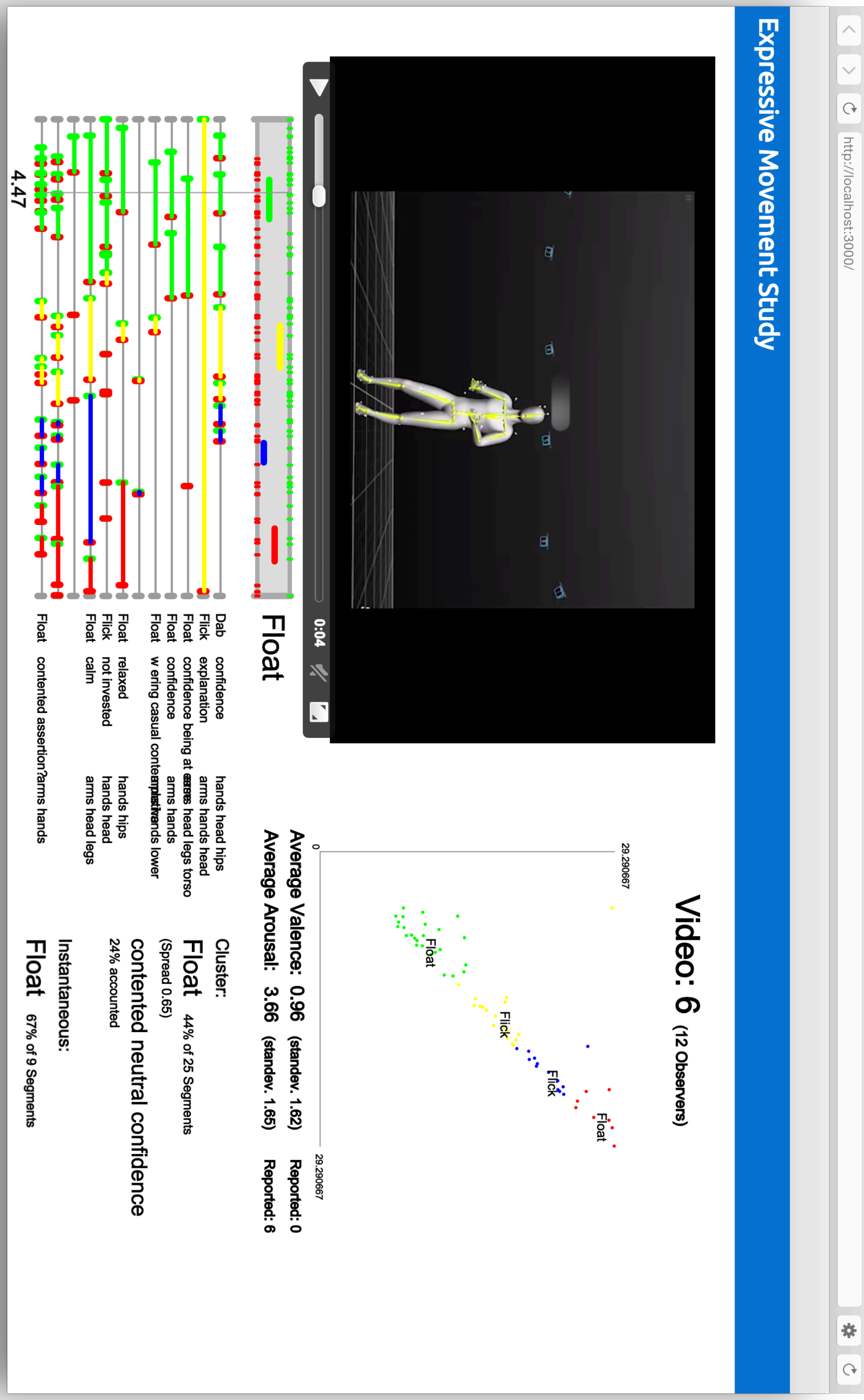

Figure 12: Pilot 2 Visualization

APPENDIX F: HUMAN SUBJECTS RESEARCH CERTIFICATION

COLLABORATIVE INSTITUTIONAL TRAINING INITIATIVE (CITI PROGRAM)

COURSEWORK REQUIREMENTS REPORT*

* NOTE: Scores on this Requirements Report reflect quiz completions at the time all requirements for the course were met. See list below for details. See separate Transcript Report for more recent quiz scores, including those on optional (supplemental) course elements.

- **Name:** Caitlin Sikora (ID: 5610287)
- **Email:** cas836@nyu.edu
- **Institution Affiliation:** New York University (ID: 1689)
- **Institution Unit:** Integrated Digital Media
- **Phone:** 4104916605

- **Curriculum Group:** Social & Behavioral Research - Basic/Refresher
- **Course Learner Group:** Same as Curriculum Group
- **Stage:** Stage 1 - Basic Course
- **Description:** Choose this group to satisfy CITI training requirements for Investigators and staff involved primarily in Social/Behavioral Research with human subjects.

- **Report ID:** 19875547
- **Completion Date:** 06/14/2016
- **Expiration Date:** 06/13/2020
- **Minimum Passing:** 80
- **Reported Score*:** 99

REQUIRED AND ELECTIVE MODULES ONLY	DATE COMPLETED	SCORE
New York University (ID: 13807)	06/13/16	No Quiz
Belmont Report and CITI Course Introduction (ID: 1127)	06/13/16	3/3 (100%)
Students in Research (ID: 1321)	06/13/16	5/5 (100%)
History and Ethical Principles - SBE (ID: 490)	06/13/16	5/5 (100%)
Defining Research with Human Subjects - SBE (ID: 491)	06/13/16	5/5 (100%)
The Federal Regulations - SBE (ID: 502)	06/14/16	5/5 (100%)
Assessing Risk - SBE (ID: 503)	06/14/16	5/5 (100%)
Informed Consent - SBE (ID: 504)	06/14/16	5/5 (100%)
Privacy and Confidentiality - SBE (ID: 505)	06/14/16	5/5 (100%)
Research with Prisoners - SBE (ID: 506)	06/14/16	5/5 (100%)
Research with Children - SBE (ID: 507)	06/14/16	5/5 (100%)
Research in Public Elementary and Secondary Schools - SBE (ID: 508)	06/14/16	5/5 (100%)
International Research - SBE (ID: 509)	06/14/16	5/5 (100%)
Internet-Based Research - SBE (ID: 510)	06/14/16	5/5 (100%)
Research and HIPAA Privacy Protections (ID: 14)	06/14/16	5/5 (100%)
Vulnerable Subjects - Research Involving Workers/Employees (ID: 483)	06/14/16	4/4 (100%)
Conflicts of Interest in Research Involving Human Subjects (ID: 488)	06/14/16	4/5 (80%)

For this Report to be valid, the learner identified above must have had a valid affiliation with the CITI Program subscribing institution identified above or have been a paid Independent Learner.

CITI Program
Email: citisupport@miami.edu
Phone: 305-243-7970
Web: https://www.citiprogram.org

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