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The Dance of Emotion: Demonstrating Ubiquitous Understanding of Human Motion and Emotion in Support of Human Computer Interaction

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***Abstract*—Appreciating the importance of robust understanding of human motion and its emotional intention, this research assesses the relevance of the Laban Effort system in classifying movement quality as it applies to the design of gestural interfaces. Labeling of Laban Efforts and affect in human motion by 14 participants demonstrated that non-expert humans can recognize a subset of the Laban Efforts with a reasonable degree of inter-rater reliability–ICC(2,k)=0.78–and validity–F1-Score=0.76. This study also includes a preliminary exploration of relationships between different emotions and Laban Efforts.**

1. Introduction

With mounting evidence that body expression is as significant to communication of affect and intention between humans as other modalities–such as facial expression and voice [1]-[5], researchers have become interested in the development of systems for classifying and interpreting body language [6]-[9]. Harnessing the power of human movement as a medium for communication in the context of technology has applications in the design of more sensitive assistive technologies, more perceptive smart homes, and more capable social robots and conversational agents [6], [10]-[17]. As Kleinsmith and Bianchi-Berthouze point out, the ability to accurately and automatically interpret states of user affect and intention will leverage body movement as "…not only a means to control the interaction… but also a way to capture and affect our own emotional and cognitive performances" [6]. In order to more fully realize this vision, we must improve our understanding of how humans imbue and extract meaning in, and from, body movement.

Traditional linguistic and cognitive science approaches to interpreting meaning from movement tend to consider shapes of specific, often culturally defined gestures, timing of gestures with speech, and spatial referencing of deictic gestures (pointing) [18]-[23]. Current gestural interfaces echo this line of reasoning with one-to-one associations of mechanically specific movements and deictic gestures dominating the design of movement-based interactions [24][25]. For example, Wii and Kinect video games extend the direct manipulation paradigm of the mouse to include a greater portion of the body, which is used to control aspects of the game environment with predetermined gestures. Execution of such gestures must be performed intentionally, but literature in the cognitive sciences indicates that non-verbal communication and interpretation are not always performed consciously–as evidenced by accidental behaviors in deceptive communication, for instance [26][27]–or processed consciously [28]. Imagine the possibilities created by a system that can respond to what you communicate through non-conscious physical expression.

Recently, a number of methods for classifying gesture have been created to capture emotional state and intention communicated non-consciously through everyday human movement in natural contexts [6]. However, many of these classification systems–including the Body Action and Posture coding system [7]–do not consider the quality with which a movement is performed. Several research groups have made efforts to consider movement quality [8], [29]-[31], but their vocabulary is generally limited to 'expandedness', 'fluidity', and 'velocity' or 'energy' [6]. We propose leveraging existing methodologies from the field of dance to consider more nuanced qualities. Dance is a discipline that has deep expertise in the expression and interpretation of human movement and emotion. The study of Laban Movement Analysis offers a system for classifying movement quality that can be generalized to establish a rich lexicon of detectable, expressive qualities to inform the design of movement-based interfaces.

In this paper, we conduct an empirical study to assess the relevance of the Laban Effort system for classifying movement quality to the design of gestural interfaces. Non-expert participants labeled video recordings of human movement with both Laban Efforts and emotional intention. Results demonstrate that (1) humans can reliably recognize a subset of the Laban Efforts, and (2) several of the Laban Efforts are associated with emotional intention.

2. Related Work

2.1. Movement Analysis in Lingustics

Influenced by Efron's ground-breaking insights on gesture as language [18][19], Ekman and Friesen created a

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system for classifying nonverbal behavior, which distinguishes between "expressions of emotion, regulators, adaptors, illustrators, and emblems" [19]. As Ekman writes: *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 that co-occur with speech to illustrate the idea being expressed (e.g., indicating the size or shape of an object with one's hands or deictic gestures); *Emblems* are culturally specific non-verbal signals that can be directly translated into words, such as the ok-symbol or thumbs up; and *Emotional expressions* are signals of an emotional experience (e.g., facial expressions, postural shifts, etc.) [20].

In a similar approach to that of Ekman and Friesen, Kendon extracts 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 [21]. In line with his studies that temporally tie gesture to co-occurring speech, Kendon arranges gestures into classes according to their interchangeability with words.

Informed by the work of their predecessors, McNeill and Levy also conform to the viewpoint that movements must be interpreted in conjunction with co-occurring speech [22]. 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" [23].

Collectively, McNeill, Levy, Kendon, Ekman, Friesen, and Efron provide tools for analyzing the meaning of movements in their conversational contexts. 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.

2.2. Perception of Meaning from Movement

Michotte's landmark research on perception of causality from moving visual stimuli used subject-reported percepts on animations of moving geometric objects to demonstrate that causal relationships are almost universally perceived by observers in simple movements [28]. 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" [28]. As Scholl and Tremoulet suggest, the most important contribution of Michotte may be the knowledge that there are "specific conditions" of movement that lead to the perception of causality [28]. Extending this work, Heider and Schimmel used similar methods to demonstrate that humans are likely to interpret personality traits and emotions–even genders and specific intentions [32]– from the movement of abstract objects in animations [28]. This evidence suggests that movement itself is a medium by which affect, personality, and intention are communicated. Bassili's related research reveals that movement patterns are also indicators of animacy [28].

Evidence from the cognitive sciences substantiates the idea that emotional experience and intention can be gleaned purely from movement, but traditional linguistic models for classification of gesture are limited to consideration of 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. This analysis of movement does not account for the full range of interpretation observed by researchers like Michotte, and it is reasonable to look to other disciplines to uncover the logic underlying such interpretation. The quality with which a body part moves through space over time is considered more thoroughly in the field of dance, specifically in Laban Movement Analysis.

2.3. Laban Movement Analysis and Effort

Laban Movement Analysis (LMA) provides a system for describing characteristics of individual movements and phrases according to four Affinities: Shape, Effort, Body, and Space (capitalized according to Laban conventions and indicating reference to specific definitions). Shape is primarily concerned with position and pathway (change in position over time) of body parts [33]. 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, Upper-Lower, Core-Distal, Head-Tail, Body-Half, and Cross-Lateral [34].

The Space Affinity considers the placement of body parts in space, especially relative to the body's center. It 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 [35].

The Effort Affinity provides a system for classifying movement quality. It 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 is 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) [36].

Because the Laban Efforts play a significant role in this research, it is important to gain a sense for each of the above factors. 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. 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 long time. This is dependent upon the definition of a scale or point of reference, which is usually defined by the gestural phrase in which a movement occurs. 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. 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 [36].

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 unique combination of specific values for the Time, Space, and Weight factors visible in Table I [36]. These Efforts are particularly useful in connecting intention to the quality of a movement as their titles communicate both quality and aim. LMA–in contrast with many classification systems proposed by linguists– outlines a variety of communicative features of movement that can be extracted and interpreted separately from any accompanying speech.

TABLE I. LABAN EFFORTS

Effort	Time	Space	Weight	Description
Punch	Quick	Direct	Heavy	Defined, hard stops, clear path
Dab	Quick	Direct	Light	Defined, smooth stop, clear path
Slash	Quick	Indirect	Heavy	No clear stops, smooth follow-through
Flick	Quick	Indirect	Light	Easy, no clear stops, rebounds from edges
Press	Sustained	Direct	Heavy	Effortful, clear path and destination
Glide	Sustained	Direct	Light	No clear stops, smooth follow-through
Wring	Sustained	Indirect	Heavy	Effortful, no clear stop
Float	Sustained	Indirect	Light	Easy, no clear stop

2.4. Movement Quality and HCI

Researchers since the 1970s have been concerned with the use of movement in the presentation and manipulation of signifiers on computer screens. Atkinson's famous marching ant pattern–used to indicate selection of an area on the screen [37]–and jumping icons–used for alerts–provide examples of the successful integration of movement as a communicator in screen-based interfaces. More recently, researchers such as Mutlu and colleagues have begun to investigate the design of movement on the screen to elicit affect and/or communicate emotional intentions [38]. The applications of such research reach beyond traditional screen-based systems.

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 technology can also influence the user through the physical movements required to interact with the system. Several scholars and designers have already begun to consider the use of Laban Efforts in the design of touch-based interfaces to elicit particular emotional responses [39][40]. Other scholars have begun investigations of movement quality as it can be used in interactions with robots, social avatars, and even drones [10]-[13], [41].

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, robots and other animate physical devices, and users consciously interacting with gesture-based systems. Research indicates that 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. Systems like the BAP coding system [7] and those created by Roether et al [42] and Kleinsmith et al [43] primarily consider shape-like features based on position as a means for defining movement as it indicates affect. Other systems like those of Wollbott [30], Dahl and Friberg [8] and Castellano et al [31] give greater attention to movement quality, but remain limited to ‘speed’ or ‘energy’ of a movement, expansion and shrinking (which are shape-based), and fluidity. Gross et al [29], on the other hand, gives attention to Laban’s conceptions of Time, Space, Weight, and Flow, without looking at the explicit Effort vocabulary. Several other researchers have begun to investigate the possibility of algorithmically identifying movement quality and/or affect as informed by Laban Movement Analysis. Zhao, for example, used neural networks to identify Laban Efforts from motion capture data and video [44]. 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 [44]. This study provides evidence that algorithmic classification of Laban Efforts is possible for interactive systems, but it does not address larger questions of relevance to the field of HCI.

LMA and dance vocabulary have also been used more loosely 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’s work and dance systems for analyzing movement as they created a set of meta-features for detecting expressive qualities [45][46]. This work informed Ginevra, Castellano and collaborators in their attempt to classify four states of affect in the valence-arousal space–anger, joy, pleasure, and sadness–from expressive movement [47]. It is evident from this research that movement can be used to distinguish arousal levels and identify affect in the valence-arousal space, though Castellano notes that confusion occurs between positive and negative states of the same arousal [47].

In a study by Giraud and collaborators, Laban principles guided the design of meta-features for algorithmically classifying affect. Giraud’s team recorded motion capture data for 20 students 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” [48]. The researchers used the Laban Effort-Shape framework to extract 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 [48]. Overall, they found that aroused conditions were marked by higher Energy, positive moods were consistently higher in Impulsivity, and negative moods were associated with greater tension [48]. 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.

3. Methodology

The goal of this research is to assess the reliability and validity of the Laban Efforts for interpreting emotional content encoded in a person’s movements in order to improve both bidirectional understanding and sensitivity in human-computer interaction. A framework for classifying and discussing movement quality and its relationship to emotional expression will bring us closer to developing seamless communication between humans and computers.

Guided by the approaches taken by previous researchers to establish systems for interpreting meaning from movements, we conducted a study in which participants encoded the movements of others with Laban Efforts and emotional interpretations. The study addressed two questions: (1) Do humans reliably and accurately perceive Laban Efforts in each other’s movements? (2) Do humans reliably interpret emotional intention from movements with a specific Laban Effort? If non-experts can perceive the Laban Efforts, it is likely that this classification system will be useful in identifying communicative characteristics of movement. If emotional intentions can be connected consistently with the Efforts, it is likely that this classification system or a derivative will have applications in affective computing for detecting, communicating, or influencing affect.

We created a collection of videos, in which a trained female dancer (MFA, NYU Tisch) performed movements classified by each of the eight Laban Efforts: Slash, Punch, Dab, Wring, Press, Flick, Float, and Glide. The collection included eight 30 second videos–each a sequence of mostly pedestrian movements of a single Laban Effort–and eight single-gesture videos–in which the dancer raised her hand to chest-height and toward the mid-line of her body with each of the eight Efforts as shown in Fig. 1.

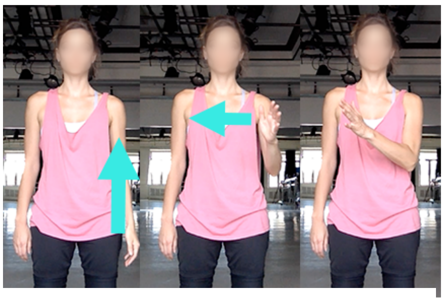

Figure. 1. Single-gesture Video Still Frames (Faces were not blurred in the actual study.)

Videos were encoded by 7 males and 7 females in their 20s–a mixture of non-experts, some with movement training and some without, from various geographic and cultural backgrounds. Initially, each participant was asked to label each of the eight long videos with a Laban Effort and 1-2 words for emotional interpretation. To allow maximum range of emotional interpretations, subjects were asked to provide free-form responses for emotional labeling of videos. At this point, participants were asked to watch a 1min. 43sec. video introducing the Laban Affinities of Time, Space, and Weight with demonstrations of the polarities of each. Table I, which defines each of the eight Efforts as a unique combination of values for each Affinity, was also presented. Then, the initial labeling process was repeated with the same videos to control for the effects of both obscure terminology and the learning curve involved in understanding the classification system. 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.

In total, 14 participants assessed 16 video segments, yielding 224 classifications for evaluation. In the pre-training classification–before the introduction to LMA, one participant left the survey blank. In the post-training classification–after the introduction to LMA, three participants missed at least one label. Participants with missing data were excluded from analysis, resulting in 208 classifications in the pre-training data set and 154 classifications in the post-training data set.

For analysis of inter-rater reliability, a two-way random effects model known as ICC(2,k) was implemented according to Shrout and Fleiss [49]. This measure models both the effect of raters and of rated motions (i.e. two effects) and assumes both are drawn randomly from larger populations (i.e. a random effects model). This statistic corroborates our choice of study design, which uses constant raters for all movement video segments, and we assume our participants are randomly drawn from potential technology users. Mean rater agreement, the coefficient of total agreement between video raters of Laban motion was calculated using R package "*psych*" [50]. Interpretation of ICC(2,k) is based on previously published heuristics, with ranges between 0.60 and 0.74 as "good" and between 0.75 and 1.0 as "excellent" [51].

For evaluation of classification accuracy, we generated a vector containing actual multi-class labels for each video segment as a testing reference standard, and assessed accuracy of the rater assignment of classes as scored by raters using our entire pre-training data (n=208) and post-training data set (n=154). We report macro-averaged F1 score, precision and recall to quantify the validity of rater classifications to accurately classify the reference standard. The macro-F1 gives equal weight to all classes (this study has 8 classes), ensuring that poor performance on the minority class is not masked by good performance on the majority class. Class-specific F1 scores are reported to identify areas where users may have more difficulty interpreting movement.

To determine the effect of the rater training on classification performance, we randomly sampled between 10% and 90% of the labeled data, and evaluated the pre-training and post-training rater classification on the testing reference standard. We sampled the original dataset 10,000 times, generating an empirical distribution of macro-F1 scores that we use to assess the difference in classifier performance between pre- and post-training on Laban classification and report the statistic for a 2-sided t-test.

4. Results

The results from the study indicate that individuals who are not trained in dance are indeed capable of reliably perceiving Laban Efforts in each other's movements with a reasonable amount of accuracy. In Table II which shows the confusion matrix before the training in Laban, we observe that Float and Glide, Dab and Press, Wring and Float, and Slash and Punch are the most commonly confused pairs. In Table III, ICC(2, k) values of 0.78 and 0.80 before and after a brief introduction to LMA indicate excellent inter-rater reliability. Macro-F1 scores of 0.76 and 0.65 before and after the introduction respectively indicate significant accuracy of classification, which decreases slightly after the Laban introduction. In Table IV, among the pre-training group, we observe that the Flick motion has the most accurate classification, with macro-F1 score of 0.96; and Wring has the worst performance with a 0.57 macro-F1 score. Float and Glide categories experience the largest decrease in classification success after training.

TABLE II. LABAN EFFORT CONFUSION TABLE

	Predicted							
Actual	***Dab***	***Flick***	***Float***	***Glide***	***Press***	***Punch***	***Slash***	***Wring***
Dab	15	0	0	1	10	0	0	0
Flick	0	25	0	1	0	0	0	0
Float	0	0	20	2	0	0	0	4
Glide	0	0	4	20	1	0	0	1
Press	0	0	0	1	23	0	0	2
Punch	1	1	0	1	0	22	1	0
Slash	0	0	0	0	0	6	20	0
Wring	1	0	8	2	1	0	1	13

TABLE III. OVERALLEFFORT RELIABILITY AND VALIDITY

	ICC(2,k)	***Macro-Precision***	***Macro-Recall***	***Macro-F1***
Pre-Training	0.78	0.78	0.76	0.76
Post-Training	0.80	0.66	0.65	0.65

TABLE IV. CLASS SPECIFIC LABAN VALIDITY

	Pre-Training			**Post-Training**			
	Prec.	***Rec.***	***F1***	***Prec.***	***Rec.***	***F1***	***ΔF1***
Dab	0.88	0.58	0.70	0.78	0.54	0.64	-0.06
Flick	0.96	0.96	0.96	0.89	0.92	0.91	-0.06
Float	0.63	0.77	0.69	0.41	0.50	0.45	-0.24
Glide	0.71	0.77	0.74	0.42	0.44	0.43	-0.31
Press	0.66	0.88	0.75	0.63	0.77	0.69	-0.06
Punch	0.79	0.85	0.81	0.71	0.85	0.77	-0.04
Slash	0.91	0.77	0.83	0.95	0.73	0.83	-0.01
Wring	0.65	0.50	0.57	0.52	0.42	0.47	-0.10

5. Analysis

The Welch Two Sample t-test (unpaired, unequal variance), yields p-value of <0.001, indicating significant differences between pre-training and post-training classification, with naïve participants performing better before training. ICC(2,k) is 0.78 before the introduction and 0.80 after the introduction, where macro-F1 score is 0.76 before the introduction to Laban and falls to 0.65 after the introduction. This indicates that responses were less accurate in the post-training data, despite being as consistent as the pre-training responses. The most likely explanation for this trend is that intuitive perception of movement may be more reliable than thoughtful investigation; investigation may present opportunities to overanalyze. This conjecture is supported by the theory that interpretation of movement occurs at least partly at the perceptual level of processing.

In Tables II and V, we observe relationships between different Efforts and identify which Efforts might be most universally identifiable, possibly indicating significance in emotional expression. Flick, Slash, Punch, and Press are most consistently identified with 0.96, 0.83, 0.81, and 0.75 macro-F1 scores before the introduction to Laban. It is likely that these are most universally identified and interpreted. By looking at the confusion matrix, we can see that Wring, Float, and Glide seem to be most often confused with each other, with Punch and Slash, as well as Dab and Press, also confused. It is possible that these Efforts should be combined or otherwise redistributed to create a movement quality classification system optimized for interpreting affect.

The preliminary emotive qualities of the Laban Efforts appear to be consistently expressive, though further data is needed to draw concrete conclusions. As illustrated in Table V, Dab consistently communicates apathy or hesitation, Glide communicates ease, Flick communicates playfulness or lightness, and Slash and Punch communicate aggression. More broadly, Sustained movements and Light movements are generally interpreted

TABLE V. EMOTIONAL INTERPRETATION

Time: Sustained							
Weight: Heavy				**Weight: Light**			
Space: Direct		***Space: Indirect***		***Space: Direct***		***Space: Indirect***	
Press	#	***Wring***	#	***Glide***	#	***Float***	#
Fixated, Focused, Determined	6	Cautious, Inhibited, Restricted	5	Easeful, Free, Uninhibited	5	Aloof, Regal, Confident	6
Bored, Dismissive, Halfhearted	4	Dull, Malaise, Melancholy	4	Affectionate, Reassuring, Comfort	3	Relaxed, Peaceful, Tranquil	5
Heavy, Push, Resistant	4	Luxuriant, Reveling, Sensual	3	Dull, Sad, Disinterested	3	Ease, Free	3
Time: Quick							
Weight: Heavy				**Weight: Light**			
Space: Direct		***Space: Indirect***		***Space: Direct***		***Space: Indirect***	
Punch	#	***Slash***	#	***Dab***	#	***Flick***	#
Angry, Mad	7	Angry, Mad	7	Apathetic, Uncaring Disinterested	5	Happy, Playful, Excited	6
Perturbed, Peeved, Frustrated	5	Frustrated, Annoyed	4	Tentative, Uncertain, Hesitant	5	Soft, Light, Whimsical	3
Aggressive, Combative, Vengeance	3	Confident, Strong	3	Dull, Passive, Melancholy	3	Annoyed, Irked, On Edge	3

as less aroused than Quick and Heavy movements, which require more energy. All of the Sustained Efforts and most of the Light Efforts contain the word calm. We also found that Heavy movements are more likely to be interpreted as negative than Light movements. For example, Glide, Float, and Flick contain mostly positive words, where Slash, Punch, and Press contain mostly negative words.

6. Limitations

There are a few limitations to the design of this study. First, there is only one performer of a single gender 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, the study uses video as the medium for analysis, but the video data includes facial expressions and sounds of breathing. The performer held mostly neutral facial expressions, but humans are naturally expressive beings. This concern will be addressed in later studies, in which faces are obscured in all of the videos and motion capture data is animated without any gender/race/body-type identifying characteristics. Third, free-form labeling of emotional interpretation limited statistical analysis of the relationship between efforts and their emotional meanings. Future work will address this by limiting emotional classification and increasing sample size.

Two conceptual limitations of the study will guide future work: the handling of time in encoding the videos and the intentional, potentially unnatural performance of Laban Efforts in the videos. As for the former, 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 sequence. Regarding the latter concern, it is possible that non-experts can identify Laban Efforts in the movements of others, but those movements will only contain Laban Efforts if they have been intentionally performed. We are conducting a second study to investigate the segmentation of time by subjects, the labeling of specific, individual movements identified by participants, and the presence of Laban Efforts in natural expressive movement sequences.

7. Conclusions and Future Work

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

Fourteen participants classified videos of intentionally performed Laban qualities with Efforts and emotional interpretations. Participants achieved an ICC(2,k) of 0.78, indicating excellent inter-rater reliability and macro-F1 score of 0.76, indicating significant validity, without any introduction to Laban terminology. We conclude that untrained observers can identify Laban Efforts. Emotional interpretations of each Effort proved to have consistency amongst participants. It is clear that 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.

Future studies will be designed with the insights gleaned from this research. Larger sample sizes will improve statistical power. Participants will segment video of people engaged in natural expression of emotion to investigate movement quality in the context of conversation. The elimination and introduction of new qualities to the taxonomy will lead to the development of a powerful framework informed by LMA and 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. This will enable experimentation and design of movement through less cerebral methods. 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 is possible with typical interfaces that rely on pointing, stretching, and swiping.

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References

[1] M. Argyle. Bodily Communication. Methuen & Co. Ltd, 1988.

[2] P.E. Bull. Posture and Gesture. Pergamon, 1987.

[3] L. McClenney and R. Neiss, “Post-hypnotic suggestion: A method for the study of nonverbal communication,” J. Nonv. Behav, vol. 13, pp. 37-45, 1989.

[4] H. Meeren, C. van Heijnsbergen, and B. de Gelder, “Rapid perceptual integration of facial expression and emotional body language,” Proc. Nat. Acad. Sci. of the USA, vol. 102, no. 45, pp. 16518-16523, 2005.

[5] J. Van den Stock, R. Righart, and B. de Gelder, “Body expressions influence recognition of emotions in the face and voice,” Emotion, vol. 7, no. 3, pp. 487-494, 2007.

[6] Kleinsmith, Andrea, and Nadia Bianchi-Berthouze. "Affective body expression perception and recognition: A survey." *IEEE Transactions on Affective Computing* 4.1 (2013): 15-33.

[7] Dael, Nele, Marcello Mortillaro, and Klaus R. Scherer. "The body action and posture coding system (BAP): Development and reliability." *Journal of Nonverbal Behavior* 36.2 (2012): 97-121.

[8] S. Dahl and A. Friberg, “Visual perception of expressiveness in musicians’ body movements,” Music Perception, vol. 24, no. 5, pp. 433–454, 2007.

[9] G. Castellano, M. Mortillaro, A. Camurri, G. Volpe, and K. Scherer, “Automated analysis of body movement in emotionally expressive piano performances,” Music Perc, vol. 26, no. 2, pp. 103-120, 2008.

[10] C. Pelachaud, “Studies on gesture expressivity for a virtual agent,” Speech Commun, vol. 51, no. 7, pp. 630-639, 2009.

[11] R. Picard, “Toward agents that recognize emotion,” Proc. of IMAGINA, pp. 153-165, Springer-Verlag, 1998.

[12] Castro-González, Álvaro, Henny Admoni, and Brian Scassellati. "Effects of form and motion on judgments of social robots′ animacy, likability, trustworthiness and unpleasantness." *International Journal of Human-Computer Studies* 90 (2016): 27-38.

[13] Vala, Marco, et al. "From virtual bodies to believable characters." AISB Journal 1.2 (2002): 219-223.

[14] Conn, Karla, et al. "Affect-sensitive assistive intervention technologies for children with autism: An individual-specific approach." *Robot and Human Interactive Communication, 2008. RO-MAN 2008. The 17th IEEE International Symposium on*. IEEE, 2008.

[15] Garay, Nestor, et al. "Assistive technology and affective mediation." *Human Technology: an Interdisciplinary Journal on Humans in ICT Environments* (2006).

[16] Miskelly, Frank G. "Assistive technology in elderly care." *Age and ageing* 30.6 (2001): 455-458.

[17] Cortés, Ulises, et al. "Assistive technologies for the disabled and for the new generation of senior citizens: the e-Tools architecture." *AI Communications* 16.3 (2003): 193-207.

[18] Efron, David. Gesture and Environment: A Tentative Study of Some of the Spatio-Temporal and "linguistic" Aspects of the Gestural Behavior of Eastern Jews and Southern Italians in New York City, Living Under Similar As Well As Different Environmental Conditions. New York: King's crown Press, 1941. Print.

[19] Johnson, Harold G., Paul Ekman, and Wallace V. Friesen. "Communicative body movements: American emblems." *Semiotica* 15.4 (1975): 335-354.

[20] Ekman, Paul. "Emotional and conversational nonverbal signals." *Language, knowledge, and representation*. Springer Netherlands, 2004. 39-50.

[21] Kendon, A. 2004. Gesture: Visible Action as Utterance. Cambridge: Cambridge University Press.

[22] McNeill, David. "Gesture: a psycholinguistic approach." *The encyclopedia of language and linguistics* (2006): 58-66.

[23] McNeill, David. *Hand and mind: What gestures reveal about thought*. University of Chicago press, 1992.

[24] Bhuiyan, Moniruzzaman, and Rich Picking. "Gesture-controlled user interfaces, what have we done and what's next." Proceedings of the Fifth Collaborative Research Symposium on Security, E-Learning, Internet and Networking (SEIN 2009), Darmstadt, Germany. 2009.

[25] Saffer, Dan. Designing gestural interfaces: Touchscreens and interactive devices. " O'Reilly Media, Inc.", 2008.

[26] P. Ekman, "Mistakes When Deceiving," Annals of the New York Academy of Sciences, vol. 364, pp. 269-278, 1981.

[27] J. E. Hocking and D.G. Leathers, "Nonverbal indicators of deception: A new theoretical perspective," Communication Monographs, vol. 4, no. 2, pp. 119-131, 1980.

[28] Scholl, Brian J., and Patrice D. Tremoulet. "Perceptual causality and animacy." *Trends in cognitive sciences* 4.8 (2000): 299-309.

[29] M.M. Gross, E.A. Crane, B.L. Fredrickson, "Methodology for Assessing Bodily Expression of Emotion," J Nonv Behav, vol. 34, pp. 223–248, 2010.

[30] H.G. Wallbott, "Bodily expression of emotion," European Journal of Social Psychology, vol. 28, pp. 879-896, 1998.

[31] G. Castellano, M. Mortillaro, A. Camurri, G. Volpe, and K. Scherer, "Automated analysis of body movement in emotionally expressive piano performances," Music Perc, vol. 26, no. 2, pp. 103-120, 2008.

[32] Dittrich, Winand H., and Stephen EG Lea. "Visual perception of intentional motion." *Perception* 23.3 (1994): 253-268.

[33] Lamb, Warren. Posture and gesture: An introduction to the study of physical behaviour. G. Duckworth, 1965.

[34] Bartenieff, Irmgard, and Dori Lewis. *Body movement: Coping with the environment*. Psychology Press, 1980.

[35] Dell, Cecily, Aileen Crow, and Irmgard Bartenieff. *Space harmony : basic terms*. New York: Dance Notation Bureau Press, 1977. Print.

[36] Laban, Rudolf, and F. C. Lawrence. "Effort London: MacDonald & Evans." (1947).

[37] Cook, Matthew Thomas. A 3-dimensional Modeling System Inspired by the Cognitive Process of Sketching. ProQuest, 2007.

[38] Mutlu, Bilge, et al. "The use of abstraction and motion in the design of social interfaces." *Proceedings of the 6th conference on Designing Interactive systems*. ACM, 2006.

[39] Lepore, Traci. "Laban Movement Analysis for User Experience Design." *UXmatters*. 22 Feb. 2016. Web. 12 Sept. 2016.

[40] Sicchio, Kate. "Laban Principles for UX Design." Fjord. 12 June 2015.

[41] Cauchard, Jessica R., et al. "Emotion Encoding in Human-Drone Interaction."*2016 11th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*. IEEE, 2016.

[42] C. Roether, L. Omlor, A. Christensen, M.A. Giese, "Critical features for the perception of emotion from gait," Journal of Vision, vol. 8, no. 6:15, pp. 1-32, 2009.

[43] A. Kleinsmith, N. Bianchi-Berthouze, "Recognizing Affective Dimensions from Body Posture," Proc Int. Conf. of Affective Computing and Intelligent Interaction, LNCS 4738, pp. 48-58, 2007.

[44] Zhao, Liwei, and Norman I. Badler. "Synthesis and acquisition of laban movement analysis qualitative parameters for communicative gestures." University of Pennsylvania (2001).

[45] Camurri, Antonio, Barbara Mazzarino, and Gualtiero Volpe. "Analysis of expressive gesture: The eyesweb expressive gesture processing library." *International Gesture Workshop*. Springer Berlin Heidelberg, 2003.

[46] Camurri, Antonio, Barbara Mazzarino, and Gualtiero Volpe. "Expressive interfaces." *Cognition, Technology & Work* 6.1 (2004): 15-22.

[47] Castellano, Ginevra, Santiago D. Villalba, and Antonio Camurri. "Recognising human emotions from body movement and gesture dynamics." *International Conference on Affective Computing and Intelligent Interaction*. Springer Berlin Heidelberg, 2007.

[48] Giraud, Tom, et al. "Impact of elicited mood on movement expressivity during a fitness task." *Human Movement Science* 49 (2016): 9-26.

[49] Shrout, Patrick E., and Joseph L. Fleiss. "Intraclass correlations: uses in assessing rater reliability." *Psychological bulletin* 86.2 (1979): 420.

[50] Revelle, W. (2017) psych: Procedures for Personality and Psychological Research, Northwestern University, Evanston, Illinois, USA, https://CRAN.R-project.org/package=psych Version = 1.7.5.

[51] Cicchetti, Domenic V. (1994). "Guidelines, criteria, and rules of thumb for evaluating normed and standardized assessment instruments in psychology." Psychological Assessment. **6** (4): 284–290.