

# Laban Movement Analysis and Affective Movement Generation for Robots and Other Near-Living Creatures

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**Abstract** This manuscript describes an approach, based on Laban Movement Analysis, to generate compact and informative representations of movement to facilitate affective movement recognition and generation for robots and other artificial embodiments. We hypothesize that Laban Movement Analysis, which is a comprehensive and systematic approach for describing movement, is an excellent candidate for deriving a low-dimensional representation of movement which facilitates affective motion modeling. First, we review the dimensions of Laban Movement Analysis most relevant for capturing movement expressivity and propose an approach to compute an estimate of the Shape and Effort components of Laban Movement Analysis using data obtained from motion capture. Within a motion capture environment, a professional actor reproduced prescribed motions, imbuing them with different emotions. The proposed approach was compared with a Laban coding by a certified movement analyst (CMA). The results show a strong correlation between results from the automatic Laban quantification and the CMA-generated Laban quantification of the movements. Based on these results, we describe an approach for the automatic generation of affective movements, by

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adapting pre-defined motion paths to overlay affective content. The proposed framework is validated through cross-validation and perceptual user studies. The proposed approach has great potential for application in fields including robotics, interactive art, animation and dance/acting training.

## 1 Motivation

Every day we interpret others' expressions by observing their body language. Suppose only the arm and hand are visible; there is no head, face, or torso available for any revealing clues. Now imagine that the arm and hand have been transformed into a sculptured frond. It consists of many joints with bits of flexible plastic feathery "muscles" attached. It moves in hand-like waves. Does it affect you? Is it possible to translate emotional expression through the body, via algorithms, into a moving sculpture "with feelings"? This sculpture and associated questions illustrate our motivation. It is one of the immersive, responsive sculptures in a series entitled: *Hylozoic Ground*, by Philip Beesley and Rob Gorbet. In 2010, *Hylozoic Ground* was Canada's selection at the Venice Biennale of Architecture (Fig. 1).

Hylozoism is an ancient belief that all matter is sentient. The sculpture's movements are affected by the proximity of the viewer, who becomes both audience and participant. The sculptural installations consist of a large number (from dozens to hundreds) of sensors and actuators; from the robotics perspective, the sculpture can be considered as a robot with a large number of degrees of freedom. However, unlike many robots, it is not anthropomorphic, but rather, emulates non-human natural forms, akin to a forest canopy. The sensors detect the presence and proximity of visitors and generate movements and other activation in response.



**Fig. 1** Illustration of the Hylozoic series sculpture, frond mechanisms in the foreground. Photograph by Philip Beesley, reprinted with permission

Currently, the motion generation strategy is very simple, consisting of open loop control with a random component. However, visitors do not perceive these movements to be random, rather they perceive that the movement has an emotional (affective) content, e.g. “the sculpture was happy to see me”, “it was sad” [1]. This was initially an unexpected element of the interaction. We wondered if this communication path could be used more extensively by the installation designer to choreograph a movement with an intended affective content. Since people move in response to the sculpture, would it be possible to observe their movements and interact affectively through movement? This capability may be valuable beyond artistic installations, in applications such as human-computer interaction and human-robot interaction. Our goal then was to develop a way to translate between the *movement language* of humans and the potential *movement language* of the sculpture.

As a path to reach our goal, our research focused on affective human gestures of the arm and hand, the parts of the body that would be most similar to the sculptural fronds. Variations in expressions of emotion are dependent on each individual’s *body-mind*, a word coined by Bonnie Bainbridge Cohen [2] used to reinforce the fact that the body and mind are linked together within a person. Each individual has a unique personal history that influences their movements, as does their physical construction and ability. The challenge of this study, this partnership between the science of robotics and the art of expressive movement, was to attempt to discover and distil the essence of affective movement. The engineers looked to the dance/theatre performance world, where choreographed movements are specific and repeatable with believable affective qualities, for a language to analyze and describe movement. The photographs in Fig. 2 illustrate expressive arm/hand movements choreographed to create affective responses in a theatre audience.



**Fig. 2** *Left photo* Illustrates an expansive, all-encompassing joy in dancer’s lightly held arms with controlled fingers miming repetitive quick, “talking” gestures; in contrast to the singer’s delicate precisely-focused appeal. *Right photo* Illustrates a light, sustained, fluid enclosing gesture of shy love in response to a gentle touch. (author’s personal collection)

Our approach aims to formalize and quantify the relationship between perceived movement qualities and measurable features of movements, to enable this relationship to be exploited for automated recognition and generation of affective movement. Another challenge of our research was to develop a common language and shared understanding of movement analysis between interdisciplinary research team members from the dance/choreography and engineering communities. In this monograph, we will describe our approach to motion understanding, based on insights from dance notation and computational approaches. In Sect. 2, we provide a brief overview of Laban Movement Analysis, focusing in particular on the Effort and Shape components, which are instrumental to the conveyance of affect. In Sects. 3 and 4 the design of the movement database and the data collection are described. Section 5 describes the analyst annotation procedure, which is used to generate ground truth for validating our proposed approach. Section 6 describes the proposed quantification approach and verification results. In Sect. 7, the use of the proposed approach for generating affective movements is illustrated. The Chapter ends with conclusions and directions for future work.

## 2 Laban Movement Analysis

I can't do much for you until you know how to see. -José de Creeft, sculptor

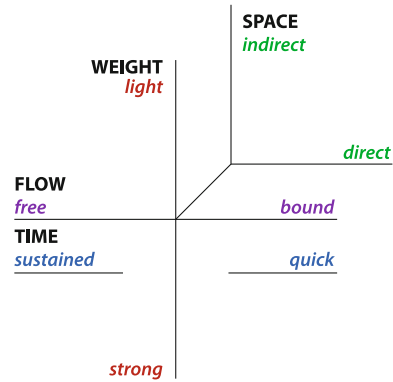
The study of Laban Movement Analysis (LMA) trains an observer to *see*, to become aware of, to attempt to ascertain the different aspects of movement. LMA promotes an understanding of movement from the inside out, as the mover, as well as from the outside in, as the observer. Rudolf von Laban (1879–1958) developed theories and systems of movement and notation. He wrote about the need to find a way to combine movement-thinking and word-thinking in order to understand the mental side of effort and action and re-integrate the two in a new form. When considering the expressive communication of the actor-dancer, Laban stressed that imitation does not “penetrate to the hidden recesses” of human inner effort. Laban searched for an authentic symbol of the inner vision in order for the performer to make effective affective contact with the audience, and felt that this could be achieved only if we have learned to think in terms of movement [3]. While attempting to capture movement in writing, he developed a system of basic principles and movement language that are encompassed in today's Laban Movement Analysis. Bloom argues “that LMA, by providing a vocabulary for articulating the detail of experiential phenomena, provides a valuable framework and a system of categories for bringing the interrelationships between body and psyche into greater focus.” [4]. To enable automated movement analysis, a computational understanding of how affect is conveyed through movement was needed. Laban Movement Analysis was used to provide a language useful in the “translation of emotions to algorithms”.

Laban Movement Analysis is divided into four overarching themes, both quantitative and qualitative. They comprise a blend of science and artistry. *Stability/Mobility* describes the natural interplay of components of the body that function to allow the full scope of human movement and balance to occur. *Exertion/Recuperation* speaks to the rhythms and phrasing of movements, that, similar to the rhythms of breath, may be said to create a “dance” between muscular tension and release. *Inner/Outer* addresses our connection from our needs and feelings within ourselves to our movement out in the world and the return flow of a response to our environment. *Function/Expression* differentiates between the aspects of movement that serve a need and the movement qualities that are expressive of affect. The latter two themes were of most interest to this project. There is some discussion amongst Certified Movement Analysts (CMAs) concerning the dichotomy between quantitative and qualitative analysis, assuming that concepts need to belong in one category or the other. The implication is that if something cannot be measured then it is qualitative and unprovable. The concepts in LMA are governed by principles, whether or not they are measurable, that make them “concrete, observable, experientially verifiable, repeatable and predictable.” [5]. For this reason, we believe LMA is amenable to computational analysis and can be related to measurable features of movement.

Laban Movement Analysis employs a multilayered description of movement, focusing on the components: Body, Space, Effort and Shape. Body indicates the active body parts, and the sequence of their involvement in the movement; Space defines where in space the movement is happening, the directions, spatial patterns and range; Effort describes the inner attitude toward the use of energy; and Shape characterizes the bodily form, and its changes in space. If each of these aspects is understood in terms of its own integrity, one can begin to comprehend how each interacts and illuminates the others [5]. Irmgard Bartenieff (1890–1981), a colleague of Laban, advocates the use of Effort and Shape as a means to study movements from behavioural and expressive perspectives. Application of the concepts of quality, or “inner attitudes towards” movement, are used in the analysis of Effort [6]. Thus among Laban components, Effort and Shape are the most relevant for our study of affective movements.

The members of our research team, in order to communicate, needed to become familiar with each other’s language, e.g., the terms “High Level-Low level” for the engineers referred to qualities of information but to the choreographer and actor, referred to placement in space. Symbols are international in a way that words are not. Laban Movement Analysis is the basis for both Labanotation and Laban Motif Notation. The choice for usage is generally based on the level of detail needed for the task at hand. Labanotation can include much detail for reproducing a movement sequence. For example, torso, shoulder, upper arm, lower arm, and separate finger gestures may be notated for precise reproduction purposes. Motif Notation is often used to capture the significant impressions, the similarities, the differences, and can lead readily to pattern recognition. In repetitive arm gestures, for example, it can be used to notate differences in various qualities or expressed efforts. Laban’s terminology and symbols become meaningful with the consciously experienced

**Fig. 3** The Laban Effort graph. The *short diagonal line* indicates Effort, and is part of every Effort symbol



embodiment of the specific movement quality. The symbols are derived from the basic Effort graph, illustrated in Fig. 3.

Table 1, adapted from Bartenieff [7] and Chi [8], illustrates different Effort qualities using simplified explanations of each of the Effort factors: Space (└), Weight (└), Time (└), and Flow (└), and their polarities or Effort elements: Space: Direct(└)/Indirect(└); Weight: Strong(└)/Light(└); Time: Sudden(└)/Sustained (└); and Flow: Bound (└)/Free (└) [9]. A simple example of arm and hand gestures provides an illustration of each of the elements. Further examples can be found in Wile [10, p. 75] and Hackney [11, pp. 219–221].

Table 2 [11, 12] illustrates examples for Laban’s Shape categories, known as Modes of Shape Change. Included are Shape Flow (≠) with two basic polarities: Growing (≠)Shrinking (≠); Directional (≠) includes Arc-like Directional (≠) and Spoke-like Directional (≠) and Shaping or Carving (≠) which includes

**Table 1** Laban Effort factors, adapted from Bartenieff [6] and Chi [7]

Effort factors	Elements	Example
Space (└): attention to surroundings	Direct (└)	Pointing to a particular spot
	Indirect (└)	Waving away bugs
Weight (└): sense of the impact of one’s movement	Strong (└)	Punching
	Light (└)	Dabbing paint on canvas
Time (└): sense of urgency	Sudden (└)	Swatting a fly
	Sustained (└)	Stroking a pet
Flow (└): attitude toward bodily tension and control	Bound (└)	Carefully carrying a cup of hot liquid
	Free (└)	Waving wildly

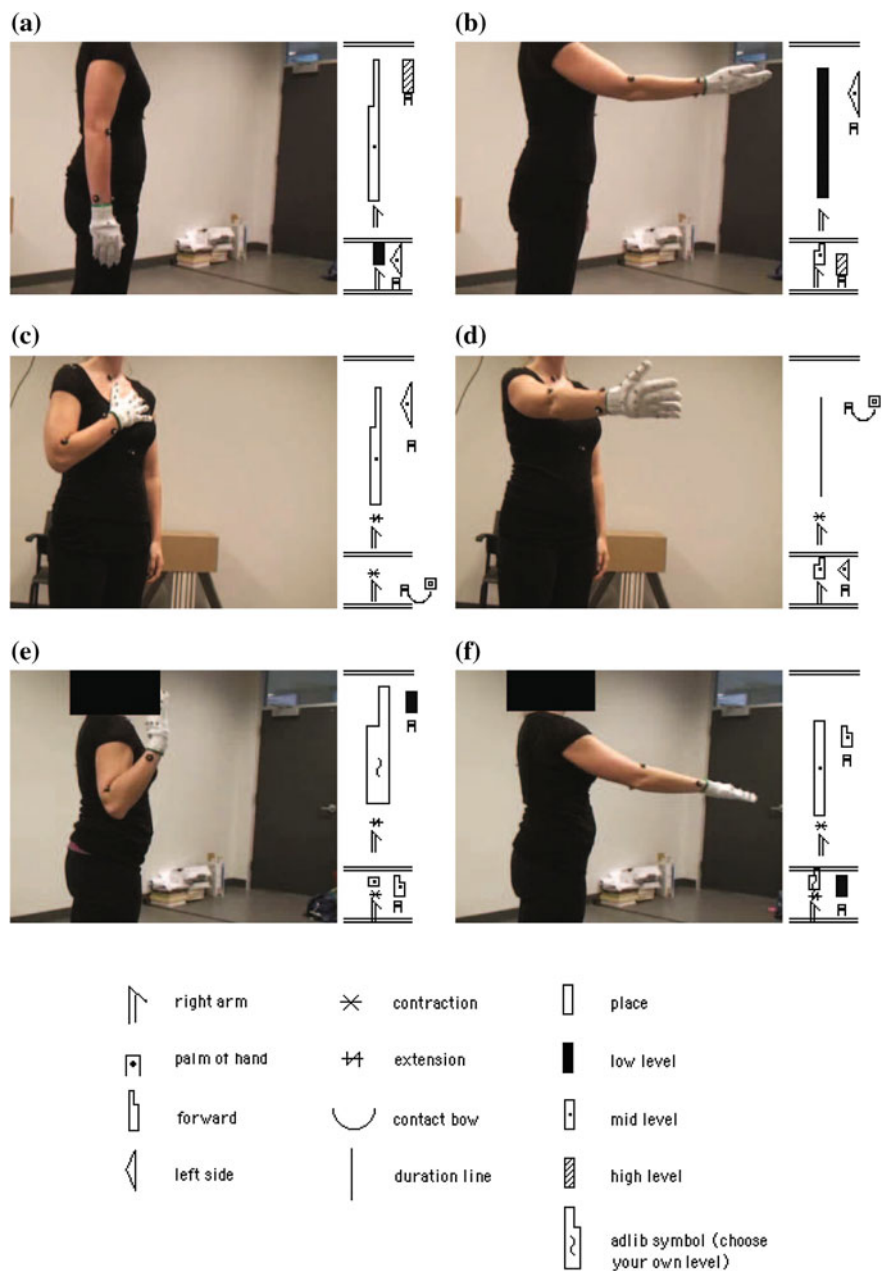
**Table 2** Laban Shape factors

Shape Factors	Elements	Example
Shape Flow (≠) is self-referential and defines readjustments of the body for internal physical comfort	Growing (—)	Self-to-self communication, stretching to yawn
	Shrinking (⌞)	Exhaling with a sigh
Directional (≠) is goal-oriented and defines the pathway to connect or bridge to a person, object, or location in space	Arc-like (≠)	Swinging the arm forward to shake hands
	Spoke-like (≠)	Pressing a button
Shaping/Carving is process-oriented and is the three dimensional “sculpting” of body oriented to creating or experiencing volume in interaction with the environment	Molding, contouring, or accommodating (≠)	Cradling a baby

three-dimensional sculptural movements. Our focus in Shape was confined to Arc-like Directional and Spoke-like Directional [9]. Further discussion of Effort and Shape notation can be found in Dell [9] and Wile [10].

### 3 Designing the Movement Pathways

In designing the movement pathways, inspiration was taken from the types of movements similar to those of the fronds in the sculpture. The goal in designing the choreographed pathways was to choose several simple arm movements that were not already strongly weighted with affect, but were as neutral as possible. Michael Chekhov (1891–1955) is known for his development of what he called the psychological gesture for actors to use for character development. Lenard Petit in his book, *The Michael Chekhov Handbook: for the actor* [13], notes that the psychological gesture is an inner gesture, found with the physical body and archetypal in form, and that five archetypal gestures are used for training purposes: pushing, pulling, lifting, throwing and tearing. These are used as a means of realizing the “six statements of action” for an actor, which are “I want - I reject, I give - I take; I hold my ground - I yield” [13]. Each of the archetypal gestures can be done in each of the six directions: forward, backward, up, down, right and left. There is different information from each of these directions and there are an infinite number of qualities (adverbs) to work with [13]. This information closely allies with Laban’s work. Genevieve Stebbins, in discussing Delsarte’s system of expression in both theory and practice, explains that there are three things to be noted in order to fully understand the motions of the arm: (1) the articulations; (2) the attitudes and (3) the inflections [14]. Interestingly, under inflections are listed: declaration, negation, rejection, caress, affirmation, appellation, acceptance, attraction, and repulsion [14]. It is important to reinforce the fact that different factors such as culture, physique,



**Fig. 4** The starting position and motif notation for each pathway. Motif notation and legend provided by Christine Heath. **a** pathway 1, **b** pathway 2, **c** pathway 3, **d** pathway 4, **e** pathway 5, **f** pathway 6, **g** motif notation legend



personal history, and specific environmental circumstances influence a quality of movement. North states that “[i]t is impossible to say either that a particular movement equals a special quality or that a particular quality equals one movement pattern plus a certain shape or space characteristic. Only generalizations can be made, because a movement assessment is made by the meticulous study of observed movement patterns of each individual.” [15]. Physical experimentation augmented the study of the literature. Kent De Spain notes that using improvisation is a form of research. It is a means of delving into the complex natural system that is the human being. In a sense, movement improvisation is another way of thinking, one that produces ideas impossible to conceive in stillness [16].

Based on the study of gestures and accompanying experimentation, three simple pathways were chosen; each was also reversed, making a total of six pathways without strong affective associations. The more limited the prescribed pathway the higher the possibility of measuring subtle significant differences between the emotions. The actor’s arm movements were to follow a given choreographed pathway in the first two of three sets. Direction along a pathway is usually significant, but this was not left free for the actor in the first and second sets. Palm facing and finger movements are also of emotional import, but variability was minimized, especially in the first set. A natural tendency to transfer expressive movements to other parts of the body, such as torso and shoulder, especially when the arm and hand movements were limited, would not be taken into account in this study due to the limitations of structure of the robotic frond.

Pathways: (1) The right arm starts down along the side, and moves up to forward mid-level, reaching, open palm facing up; (2) Similar motion as in (1) but in the reverse direction; (3) Starting with open palm on the chest, the right arm extends forward, ending with palm facing left, toward midline; (4) Similar motion to (3), but in the reverse direction; (5) Starting with the right arm bent with elbow down by the side, open palm facing forward in front of the right shoulder, the right arm extends forward at mid-level, open palm facing down, hand parallel to the floor and (6) Similar motion to (5), but in the reverse direction. (The latter two pathways were adapted by the actor to begin, or end, at a slight downward slant, between mid and low level.) The photos in Fig. 4 illustrate the beginning position and the Motif Notation for each pathway.

## 4 Motion Capture

For each of the six paths, the professional actor was asked to act each of Ekman’s original Six Basic Emotions: anger, happiness, disgust, sadness, surprise and fear [17]. Prinz acknowledges that they have become the most widely accepted candidates for basic emotions, both psychologically and biologically [18]. With five tries for each emotion, we captured 180 movement sequences (6 paths, 6 emotions, 5 trials) for each of three data sets. For data set 1: The arm-hand follows the specified path, with an attempt at no extra wrist or finger movement other than just

1. Rate the extent to which you felt you embodied the intended emotion.

	1	2	3	4	5	6	7	
Strongly disagree	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	Strongly agree

2. Rate the extent to which you felt you expressed the intended emotion.

	1	2	3	4	5	6	7	
Strongly disagree	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	Strongly agree

3. Rate the extent to which you felt another emotion emerged while demonstrating the intended affective movement.

	1	2	3	4	5	6	7	
Strongly disagree	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	Strongly agree

4. If you agree with the third question, what was the emotion that emerged?

5. Any additional comments

**Fig. 5** Questionnaire for the actor

an extension of the movement of the whole arm. For data set 2: the arm-hand follows the path, this time allowing movement of the wrist and fingers. For data set 3: the actor was allowed freedom of choice of arm and hand movements, including spatial pathway. This pilot study considered only data from data set 1.

Actors are rarely asked to “act” an emotion. Instead, actions and situations awaken emotions. The actor’s ability to create a specific emotion in this setting was

crucial to the success of this investigation. The actor relied on her rigorous training in the use of memory and imagination to freshly create and express the emotion aroused internally. In LMA, the word *intent* is used to describe part of the preparation stage of movement and “it is at this crucial point that the brain is formulating (even in a split second) the motor plan which will eventually be realized in action.” [11]. As noted in *Psychology of Dance*, the more vivid, realistic and detailed the image is, the more the senses, thoughts and emotions are involved [19]. Directly following each group of five trials, the actor was asked for her personal response as to whether she felt she had or had not embodied the intended emotion, and if another emotion had emerged instead of the specified one, what was that other emotion. As Laban notes in the introduction to his book *The Mastery of Movement*, the variety of the human character derives from the multitude of possible attitudes toward the motion factors [3]. The training of the professional actor, the number of tries, and the questionnaire shown in Fig. 5, were attempts at providing high quality motion capture examples of the six emotions.

## 5 Analysis of the Motion Capture Videos

A coding sheet was devised for the Laban Certified Movement Analyst (CMA) to use while watching the video of each movement, shown in Fig. 6. Effort elements vary in intensity ranging from slight to marked [10]. A 5-point Likert scale was used: the “0” in the centre is checked when there appears to be no significant attention by the mover to that particular Effort. The “1 and 2” on either side of the “0”, denote a noticeable increased degree of that Effort element. We focused on each of the Effort qualities: Time Effort: Sudden (↖) or Sustained (↘); Space Effort: Direct (↗) or Indirect (↙); Weight Effort: Strong (↑) or Light (↓), and Flow Effort: Bound (↖) or Free (↘). A 7-point Likert Scale was tried, but it was deemed too difficult, using video of only the arm, to translate this qualitative assessment into that much quantitative detail. There are three “levels” or opportunities for notating changes within a single movement; e.g. in Time Effort one may execute a Sudden impulse, to Timelessness or a steady time, to Sustainment or a slowing down. There is also a Comment Box for any explanatory notes deemed significant in the analysis, as shown in Fig. 6. For computing purposes, this scale was translated into a scale of 1 to 5. For the analysis of Shape, the focus was on Arc-Like (≠) or Spoke-like (≠) Directional.

We have omitted any discussion of Laban’s States (a combination of two Efforts) and Drives (a combination of three Efforts) due to the fact that the computations were based on individual Effort elements and not their combinations.

1. Laban Effort

Time \*

2

1

0

1

2

Sudden

Sustained

Sudden

Sustained

Sudden

Sustained

2. Laban Effort

Space \*

2

1

0

1

2

Direct

Indirect

Direct

Indirect

Direct

Indirect

3. Laban Effort

Weight \*

2

1

0

1

2

Strong

Light

Strong

Light

Strong

Light

4. Laban Effort

Flow \*

2

1

0

1

2

Bound

Free

Bound

Free

Bound

Free

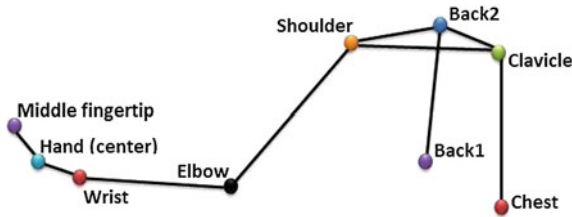
5. Laban Shape - Directional \*

Arc-like  Spoke-like

Fig. 6 Laban annotation questionnaire used by the CMA

6 Computational Laban Analysis

In addition to the longstanding research on movement analysis in the dance community, affective movement analysis has more recently also received significant attention in other domains. There is a large and active research effort on affective movement perception, recognition and generation in cognitive science, psychology, and affective computing [20]. Most closely related to our work, recently, two groups have proposed approaches for automated Laban Effort and Shape quantification. The first approach, proposed by Nakata and colleagues [21], developed a quantification approach for an aggregate set of body parts. The quantified components were used to generate dance movements, which were perceived by human observers to convey distinct affective expressions. This approach was later adopted by Hachimura et al. [22] for full-body movements, and applied to robot affective movement generation. The second approach, proposed by Kapadia et al. [23],



**Fig. 7** Marker set used for the quantification

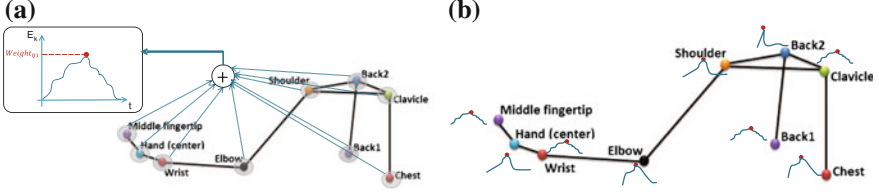
develops an approach for Laban Body, Effort and Shape quantification for individual body parts. Rather than using the approach for motion generation, Kapadia et al. use the quantification to optimize full-body motion indexing and retrieval from a motion database.

In both quantification approaches [21, 23], Laban descriptors are quantified as Boolean features,<sup>1</sup> therefore the quantification depends on the definition of suitable threshold. In our work [12], we propose a continuous quantification of LMA factors, using Nakata [21] and Kapadia [23] as the starting point. In the following, we label the approach using Nakata as the starting point as Q1, and the approach based on Kapadia as Q2. In addition, we propose quantification methods for dimensions which were not addressed by Q1 or Q2, namely a quantification for Shape: Shaping/Carving. Finally, we evaluate both proposed quantification approaches using the dataset described in Sect. 4, comparing the automated quantification with the labels generated by the expert analyst to verify the level of agreement.

Figure 7 illustrates the markers used for the quantification. These 9 markers are derived from the 30 markers used to collect data. The measured data consisted of 30 3D markers measured at 200 times per second, equaling nearly 20,000 data points for each second of video. The raw data is very high dimensional, providing a strong motivation to find a mapping between the raw data and a lower dimensional representation such as LMA, where movements can be more easily analyzed.

The first LMA factor quantified was Weight Effort ( $\text{f}$ ), which describes the sense of force of one's movement, with the contrasting elements Strong ( $\text{f}$ ) and Light ( $\text{l}$ ). Nakata et al. [21] proposed that Weight Effort be categorized based on a threshold on the kinetic energy for each body part. We adapt this approach in Q1 for a continuous valued quantification by estimating the maximum of the kinetic energy of the upper body parts, as illustrated in Fig. 8a. Kapadia et al. [23] proposed that Weight Effort be categorized based on a threshold of the deceleration of the different body part. We adapt this approach in Q2 so that the Weight Effort is

<sup>1</sup>A Boolean feature is one that can take on one of only two values, for example, True or False. In the case of LMA quantification, a Boolean feature means that each component is quantified as belonging to either one or the other of the extremum values, for example, for the component Weight Effort, each movement is classified as being either Strong or Light.



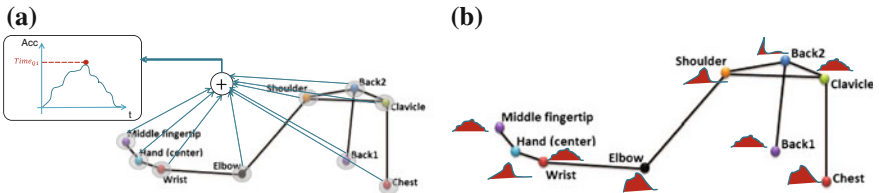
**Fig. 8** Quantifications of weight effort.  $E_k$  is the kinetic energy

quantified as the maximum of the deceleration of the different body parts, as illustrated in Fig. 8b.

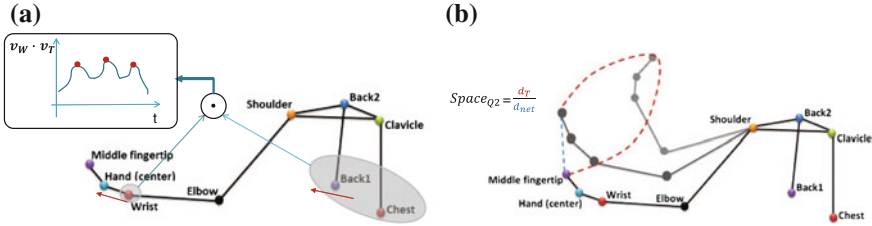
The second LMA factor quantified was Time Effort ( $\neg$ ), which describes the sense of urgency, with the contrasting elements Sudden ( $\neg$ ) and Sustained ( $\neg$ ). Nakata et al. [21] propose that the quantification for this factor be based on the acceleration of different body parts. We adapt this approach in Q1 to propose that Time Effort be quantified as the peak of the sum of accelerations of the upper body parts weighted by their relative mass, as illustrated in Fig. 9a. Q2 proposed that the Time Effort be quantified as the net acceleration accumulated at the body parts, as illustrated in Fig. 9b.

The third LMA factor quantified was Space Effort ( $\neg$ ), which describes the attention to surroundings, with the contrasting elements Direct ( $\neg$ ) and Indirect ( $\neg$ ). Nakata et al. [21] propose that the Space Effort be categorized by considering the relative direction between the torso and the face. This is implemented computationally by thresholding the inner product between the torso and face direction vectors. In Q1, this dimension is quantified by counting the number of peaks in the inner product of the tangents of the torso and wrist trajectories, as illustrated in Fig. 10a. This measure estimates how frequently the wrist trajectory changes direction relative to the torso. In Q2, Space Effort is quantified by computing the ratio of the total displacement and the net distance traveled by the body part, as illustrated in Fig. 10b.

The fourth LMA factor quantified was Flow Effort ( $\neg$ ), which describes the attitude towards bodily tension and control, with the contrasting elements Bound ( $\neg$ ) and Free ( $\neg$ ). Flow Effort was not quantified in Q1; Q2 proposed a measure of



**Fig. 9** Quantifications of time effort.  $Acc$  is the acceleration



**Fig. 10** Quantifications of space effort.  $v_W$  and  $v_T$  are the velocity of the wrist and torso.  $d_T$  is the total distance traveled, while  $d_{net}$  is the *straight line* (net) displacement from the starting to the ending pose

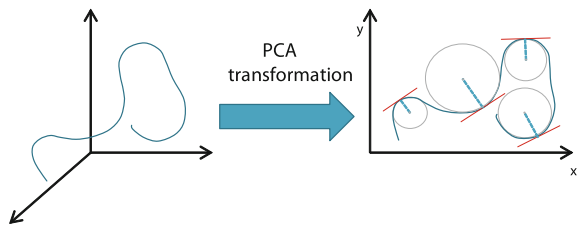
Flow Effort as the aggregated jerk over time at the considered body parts. Jerk is the rate of change of the acceleration of each body part.

The final LMA factor considered was Shape Directional ( $\neq$ ), which defines the pathway to connect to or from the demonstrator to their goal in space, with the two categories of Arc-like ( $\neq$ ) and Spoke-like ( $\neq$ ). Neither Q1 nor Q2 proposed a quantification approach for this dimension. Here, we propose to quantify Shape Directional as the average curvature of the movement in a two dimensional plane within which the largest displacement occurs. The plane of movement is estimated using the top two components found via Principal Component Analysis.<sup>2</sup> The approach is illustrated in Fig. 11.

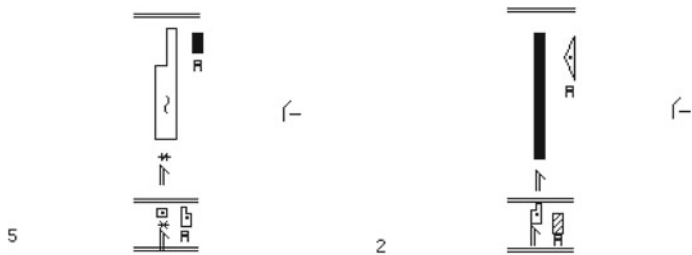
The proposed quantifications are evaluated by comparing the automated quantification values with the annotations provided by the CMA, as described in Sect. 5. A total of 44 hand and arm movements were annotated and the corresponding Effort and Shape factors quantified. As noted in Sect. 5, it was possible for the movement to contain multiple levels of each LMA component in a single movement, and the analyst had the opportunity to indicate this in her annotation by specifying multiple annotations. Movements with a variation in a single Effort factor, such as the previously mentioned example of Sudden impulse into even timing, into Sustained Time Effort, were not included. Only movements with a single annotation were considered for evaluation, to avoid the need to segment movements.

Two examples of the proposed quantification approaches are illustrated in Fig. 12. The first movement uses pathway 5, while the second movement uses pathway 2 (see Fig. 4); both are examples of angry movements. Table 3 provides the associated annotations for both the CMA and the automated approaches. As can be seen from the table, for the pathway 5 movement, the CMA indicated a Strong Weight Effort and a Sudden Time Effort. This was in good agreement with the first automated quantification approach, while the second approach incorrectly labeled

<sup>2</sup>Principal Component Analysis (PCA) is a statistical procedure for finding the directions of highest variations in a multi-dimensional dataset. In the proposed approach, PCA is used to find the plate of movement by finding the two dimensional plane where most of the movement occurs, and therefore the variance is highest.



**Fig. 11** Quantification for shape directional



**Fig. 12** Motif notation for two example movements as annotated by the CMA. Motif notation provided by Christine Heath

**Table 3** CMA and automated annotations for two exemplar movements

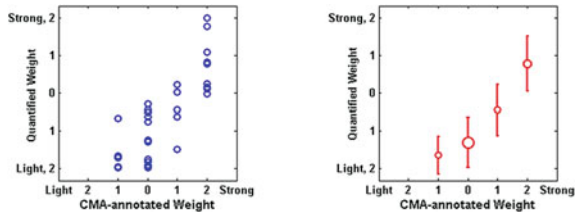
	Weight Effort			Time Effort		
	CMA	Automated Q1	Automated Q2	CMA	Automated Q1	Automated Q2
Angry pathway 5	Strong (2)	Strong (2.00)	Light (1.36)	Sudden (2)	Sudden (2.00)	Sudden (1.57)
Angry pathway 2	Strong (2)	Strong (1.09)	Light (0.09)	Sudden (2)	Sudden (1.03)	Sudden (0.73)

In each cell of the table, the label indicates the Effort element (Strong vs. Light for Weight Effort, Sudden vs. Sustained for Time Effort), while the number indicates the annotated magnitude of the element

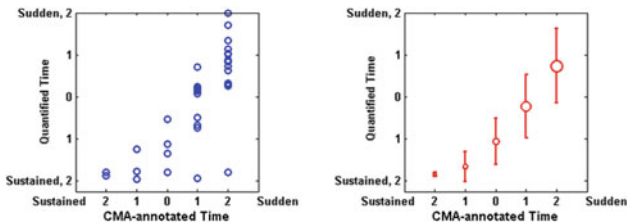
the Weight as Light. For the pathway 2 movement, the first quantification approach is in agreement with the CMA for Weight Effort (Strong), while the second approach incorrectly labels the movement as weakly Light. Both quantification approaches label the Time Effort as Sustained, in agreement with the CMA annotation.

Considering all the movements in the dataset, for the Weight Effort, high and significant correlation was found between the CMA-annotated and the quantified values, with superior performance being shown by the Q1 approach, as illustrated in





**Fig. 13** Correlation between the automated quantification Q1 and the CMA annotation for Weight Effort. The *left panel* plots the quantified Weight and the CMA-annotated Weight for each movement considered. The *right panel* shows the average and standard distribution



**Fig. 14** Correlation between the automated quantification Q1 and the CMA annotation for time effort. The *left panel* plots the quantified Time and the CMA-annotated time for each movement considered. The *right panel* shows the average and standard distribution

Fig. 13. The Pearson correlation coefficient<sup>3</sup> between the Q1 quantification and the analyst ratings for Weight Effort was found to be 81 %.

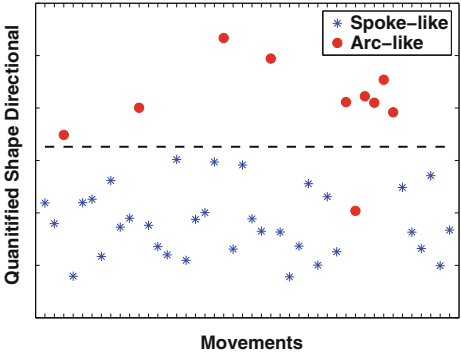
For Time Effort, the Q1 quantification approach again demonstrated superior results, with a Pearson correlation coefficient of 77 %, illustrated in Fig. 14.

For Shape Directional, a new Boolean measure was proposed, based on a threshold of the Shape Directional quantification, which successfully captures the Shape Directional element when compared to the analyst ratings, as illustrated in Fig. 15. The Phi correlation<sup>4</sup> was found to be 93 %.

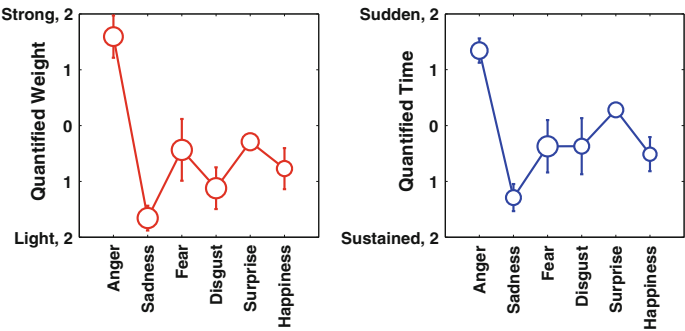
For the Space Effort factor, it was difficult to validate the proposed quantifications in the hand-arm movement dataset, due to the imbalance in the sample size, as a large majority of the movements were annotated as Direct by the CMA. Furthermore, Space Effort describes the actor’s focus (single-focused vs multi-focused) and other visual cues (eye, head movements) might be needed to better evaluate Space. For instance, an expansive hand and arm movement can be used to greet several arriving parties (multi-focused, Indirect) or a single arriving person (single-focused, Direct), which would be difficult to annotate without additional contextual information.

<sup>3</sup>The Pearson Correlation coefficient is a statistical measure of the linear dependence between two continuous variables.

<sup>4</sup>The Phi correlation is a statistical measure of the association between two binary variables.



**Fig. 15** Automated quantification and the CMA annotation for shape directional. For each movement (arranged along the *horizontal axis*), the quantified shape directional value is plotted on the *vertical axis*. The *dashed line* represents the threshold used to classify each movement as Spoke-Like (below the threshold) or Arc-Like (above the threshold). The CMA annotations for each movement are indicated by the shape of the point, *blue squares* for Spoke-Like and *red circles* for Arc-Like



**Fig. 16** Average quantified Weight and Time as a function of the emotional category. The *left panel* shows how the quantified Weight varies as a function of the emotion label, while the *right panel* shows the relationship for quantified Time. As can be seen from this plot, emotions are differentiated along these two Effort Factors

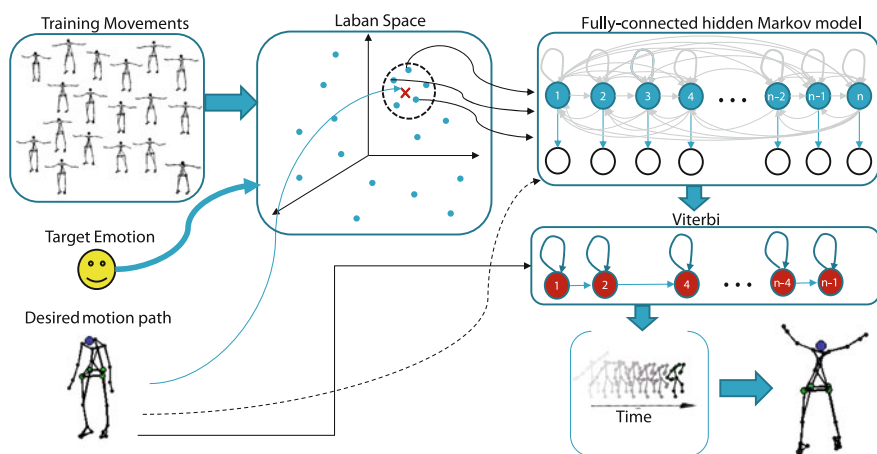
For the Flow Effort factor, the correlation between the annotated and the quantified values was found to be 67 %. However, the spatial stopping constraint in the motion paths prescribed to the actor contributes to having movements with multiple Flow qualities, as it turns a movement to Bound Flow toward the end even if it begins as a Free Flow movement.

Finally, the relationship between the quantified Laban factors and the emotional categories of the movement pathways were investigated. Figure 16 illustrates how the quantified Weight and Time factors vary for the movements in different emotion categories. These results indicate that the quantified Laban factors can be used to characterize the expressive content of the hand and arm movements.

## 7 Expressive Movement Generation

The quantification approach described in Sect. 6 is used within a data-based automated expressive movement generation framework [24]. The quantification outputs, i.e., the LMA factors, are used as a low-dimensional space where similar movements can be more easily found. The goal of the expressive movement generation approach is to imbue a given trajectory with a desired expressive content, in terms of a set of discrete emotional labels. Given a desired motion trajectory, which may or may not contain any expressive content; a target emotion label; and a database of movements with known expressive qualities, the proposed quantification is used to find similar movements (i.e., movements sharing similar Laban Effort characteristics) of the desired emotion class. The similar movements which are identified are then used to train a Hidden Markov Model [25], a stochastic dynamic model which is commonly used for modeling human movement [20]. In this type of model, the movement is modeled as a set of key postures, the spatial variation of each posture, and the dynamics of how one transitions from one posture to the next. The desired movement, consisting of the target movement with the desired affective content overlaid, is then generated using the Viterbi generation approach [25]. In this movement generation approach, the hidden Markov model is used to identify the set of key postures in the model that most closely correspond to the target movement. Then, the posture transition dynamics from the model are used to generate a smooth sequence of postures to produce a movement animation.

The proposed approach is illustrated in Fig. 17. The inputs to the algorithm are: (1) the training movement dataset, consisting of a set of movements for which the associated LMA factor quantification has been computed using the approach described in Sect. 6, and the associated emotion label for each movement; (2) the target emotion; and (3) the desired motion path. Using the LMA factor quantification,



**Fig. 17** Proposed expressive movement generation approach

the nearest neighbors (NN) of the target movement with the desired affective label in the database are identified. These movements, together with a number of copies of the target movement, are used to train a Hidden Markov model of the movement. The Viterbi algorithm is then used to generate the most likely key pose sequence in the model for the target movement, and the key pose sequence then used to generate the modified movement. The variable number of copies included in the model is a parameter that can be used to trade off the two goals of the algorithm: increasing the number of copies increases the similarity of the generated movement to the desired motion path, while decreasing the number of copies favors the target emotion over kinematic similarity.

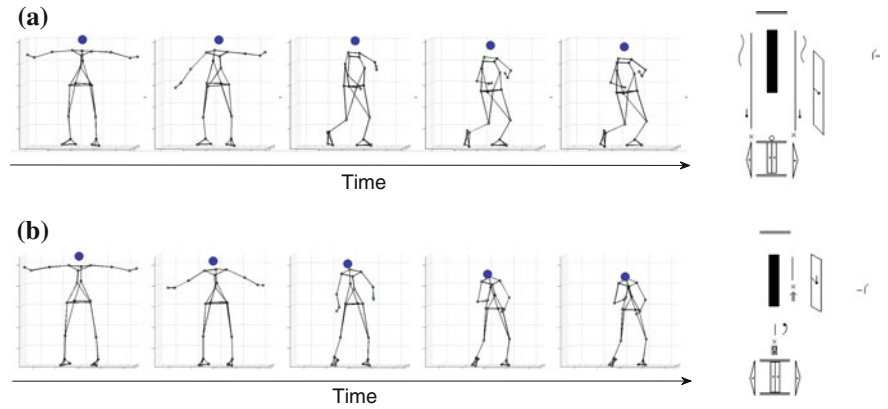
The proposed approach was validated using the UCLIC dataset [26]. The UCLIC dataset is a motion capture dataset consisting of full body movements demonstrated by 13 demonstrators, who each freely expressed movements in 4 emotional categories (sadness, anger, happiness and fear). To test the proposed affective movement generation approach, each movement in the dataset (which had an existing affective label) was used in turn as the desired motion path, and was converted to the other three affective classes. For example, each sad movement was converted to happy, angry and fearful. The generated movements were then evaluated using both an automated recognition approach [27] and by human observers in a user study.

Figures 18 and 19 illustrate two example transformations carried out using the proposed approach. In the first example (Fig. 18), a happy movement from the dataset is converted to a sad movement. In the original movement, the demonstrator's head remains upright while the right arm swings down and across with some Strength and Quickness. In the regenerated movement, the modification results in the head and chest curling forward and down while both arms swing down and closer into the chest with some Strength and Sustainment. In the second example (Fig. 19), a sad movement from the dataset is converted to an angry movement. In the original movement, the demonstrator lowers head, torso and arms down and slightly to the side with some Passive Weight and Sustainment. In the regenerated movement, the modification results in less droop of the head and chest as the hips and legs are engaged and the arms lower to down front with Strength and some Quickness.

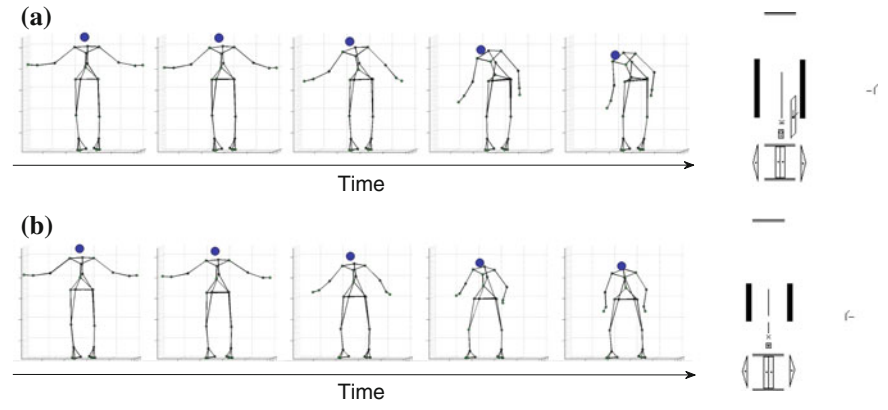
Table 4 illustrates the confusion matrix<sup>5</sup> for the automated recognition results. As can be seen from the table, the target emotion is generally correctly recognized, with an overall recognition rate of 72 %, comparable to human perception [27]. Confusions occur most frequently between Fear, Anger and Happiness, categories which share a high arousal level on the dimensional emotion model [28]. Russell [28]

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<sup>5</sup>The confusion matrix presents the recognition results in tabular form. Each row indicates the target emotion (the emotion generated by the algorithm), while each column indicates the percentage of time the target emotion was recognized as each category by the recognition algorithm. Perfect recognition would be indicated by 100 % in each diagonal cell. When there are non-zero off-diagonal elements, they indicate what type of error is being made. For example, in Table 4, fearful movement are misrecognized as angry movements 13 % of the time.



**Fig. 18** Example of a movement with an original emotion (happy) re-generated to convey a different emotion (sad). Motif Notation provided by Christine Heath. **a** Original movement (happy), **b** generated movement (sad)



**Fig. 19** Example of a movement with an original emotion (sad) re-generated to convey a different emotion (angry). Motif Notation provided by Christine Heath. **a** Original movement (sad), **b** generated movement (angry)

**Table 4** Confusion matrix for the automatic recognition of the generated movements

Target Emotions	Recognized emotion			
	Sadness	Happiness	Fear	Anger
Sadness	<b>83</b>	1	15	1
Happiness	1	<b>61</b>	22	15
Fear	3	8	<b>77</b>	13
Anger	1	15	16	<b>67</b>

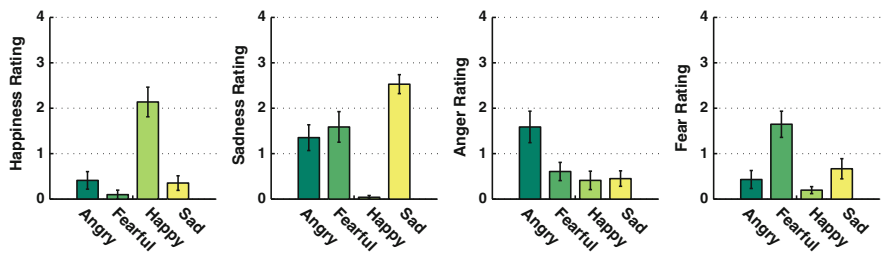


Fig. 20 Participants’ ratings when observing animations of the generated movements

postulated that the space of emotions can be represented in a two dimensional space, with the two dimensions consisting of arousal and valence. Arousal indicates the level of activation, alertness or physical activity, while valence indicates whether the emotion is positive or negative. Discrete emotional categories can be mapped to the dimensional model, for example, anger would have high arousal and negative valence, while happiness would have high arousal and positive valence. Fear, Anger and Happiness all share high arousal levels in this model.

Figure 20 illustrates the results of the user study. As can be seen in the figure, observers can generally correctly perceive the target emotion, with the target emotion receiving a significantly higher rating than the other emotions for all the motion types.

Figure 21 illustrates the interaction between the original and the target emotion during human perception of the generated movements. As can be seen in the figure, generated happy movements are perceived as happy regardless of the source movement, while for sad and angry movements, the source fear movement still retains an element of perceived fear. Fear movements could also not be successfully generated from all source movements.

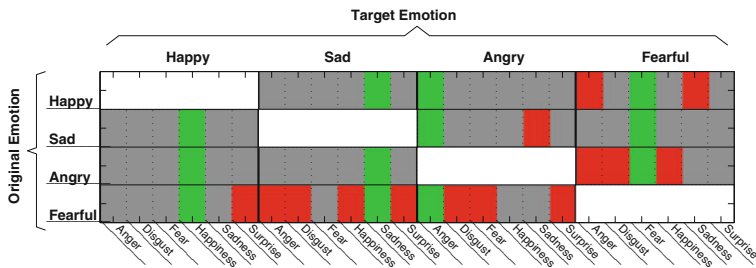


Fig. 21 A heatmap showing significance of pair-wise differences between participants’ ratings of target emotions and other emotions (paired t-tests). The green boxes highlight the target emotion, the grey boxes indicate significant differences to the ratings of the target emotion at  $p < 0.05$ , and a red box indicates that there is no significant difference to ratings of the target emotion at  $p < 0.05$

## 8 Conclusions and Future Work

Laban Movement Analysis offers a comprehensive and concise structure for representing and analyzing expressive movement, which can be of great use for characterizing and generating expressive movement for artificial agents, such as animations, kinetic sculptures and environments, and robots. In this chapter, we proposed an approach for quantifying LMA components from measurable movement features, and using the proposed quantification approach within an expressive movement generation framework. The proposed framework allows movement paths to be imbued with target affective qualities, a first step towards more expressive human-machine interaction.

We are currently working with our collaborators at Philip Beesley Architect to implement the proposed methods in a kinetic sculpture environment, to enable testing with embodied systems and online interaction.

In the future we aim to further explore the other datasets collected, where the hand, fingers and arm are not confined to specific pathways. The knowledge gleaned from further research could be used to help actors and dancers access emotional nuances through guidance and feedback in the process of discovering their own preferences and in expanding their expressive physical vocabulary of movement. Kinetic affective sculptures could be incorporated choreographically into live theatre productions. Also, Sensory Anthropology, a new academic discipline that focuses on how cultures stress different ways of knowing through brain/body maps and the senses [29], might benefit from further investigation of the generation and perception of affective movements.

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