Feature Extraction for Human Motion Indexing of Acted Dance Performances

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Abstract: There has been an increasing use of pre-recorded motion capture data for animating virtual characters and synthesising different actions; it is although a necessity to establish a resultful method for indexing, classifying and retrieving motion. In this paper, we propose a method that can automatically extract motion qualities from dance performances, in terms of Laban Movement Analysis (LMA), for motion analysis and indexing purposes. The main objectives of this study is to analyse the motion information of different dance performances, using the LMA components, and extract those features that are indicative of certain emotions or actions. LMA encodes motions using four components, Body, Effort, Shape and Space, which represent a wide array of structural, geometric, and dynamic features of human motion. A deeper analysis of how these features change on different movements is presented, investigating the correlations between the performers' acting emotional state and its characteristics, thus indicating the importance and the effect of each feature for the classification of the motion. Understanding the quality of the movement helps to apprehend the intentions of the performer, providing a representative search space for indexing motions.

1 INTRODUCTION

Motion analysis and classification is of high interest in a variety of major areas including robotics, computer animation, psychology as well as the film and computer game industries. The increasing availability of large motion databases (CMU, 2003; UTA, 2011; UCY, 2012), in addition to the motion re-targeting (Gleicher, 1998; Hecker et al., 2008) and motion synthesis (Kovar et al., 2002; Arikan et al., 2003) advancements, have contributed to the sharp increase in use of pre-recorded motion for animating virtual human characters, thus making motion indexing an essential key for easy motion composition.

Motion analysis consists of understanding different types of human actions, such as basic human actions (e.g. walking, running, or jumping) in addition to stylistic variations in motion caused by the actor's emotion, expression, gender, age etc. An important role in the description and categorisation of movements is played by the emotion, the expression and the effort of each movement, in addition to the purpose of the movement, reflecting its *nuance*. The *nuance*[1] of a movement, along with the concentration and the energy needed to carry out the action, represents the intangible characteristics, and can describe the intentions of the performer; it is the additional information that the human eye and brain use to assess and index a movement. Based on the principles of movement observation science (Moore and Yamamoto, 1988), we aim to extract the so-called nuance of motion and use it for motion indexing and classification purposes.

The movement of the human body is complex and it is not possible to completely describe the human movement language if rough simplifications in motion description are used or if motion has not been properly indexed from the outset. Laban Movement Analysis (LMA) (Maletić, 1987) is a multidisciplinary system which incorporates contributions from anatomy, kinesiology, and psychology and which draws on Rudolf Laban's theories to describe, interpret and document human movements; it is one of the most widely used systems of human movement analysis and has been extensively used to describe and document dance and choreographies over the last century. Consequently, we propose an efficient method that can automatically extract motion qualities, in terms of LMA entities, for motion analysis and indexing purposes; each movement is associated with a qualitative and quantitative description that may help to search

[1] The details of movement style in which essence or meaning is encapsulated in the proper execution of the steps" Muriel Topaz, 1986 (in Dunlop's book Dance Words).

for any correlations between different performances or actions. The main objective and novelty of this study is to analyse the motion information of different dance performances, using the LMA components, to extract those features that are indicative of certain emotions and explore how they change with regards to the performer's emotion, as referred in emotion research science (Russell, 1980). To get the users involved in a more active manner, we used acted dance data of different contemporary scenarios since the performers try to express their feelings through the dance and their movement vocabulary; the performers put more emphasis on movements since it is the only way of channelling their emotions to the public. It is important to note that this paper does not intend to document the emotions of a dance or its performer (which are subjective), but to export those features that characterise the performer's movement and are indicative to the movement quality. An analysis of how these features change on movements with different feelings is presented, investigating the correlations between the performers' acting emotional state and its characteristics; the outcomes of this work can be used as an alternative or complement to the standard methods for motion synthesis and classification. Results demonstrate the importance of each of the proposed features and their effect in the classification of motion. Understanding movement quality helps to apprehend the intentions of the performer, providing a valuable criterion for motion indexing.

2 RELATED WORK

Over the last decade, a large number of different approaches have been developed for human figure animation and motion synthesis, where the characters behave autonomously through learning and perception (Arikan et al., 2003; Fang and Pollard, 2003). Most papers in the literature synthesise new movements to enrich the motion databases by combining different motion parts and reusing existing data. They segment the human skeleton into the upper and lower body or into smaller kinematic chains and classify motions using simple vocabularies (such as walk, run, kick, box, etc.), (Kovar and Gleicher, 2004; Ikemoto and Forsyth, 2004), while other works designed vocabularies based on a specific subject (e.g. kickboxing, dancing etc.), (Kwon et al., 2008; Chan et al., 2011). (Müller et al., 2005) proposed a content-based retrieval method to compute a small set of geometric properties which are used for motion similarity purposes. Various techniques have been proposed for spatial indexing of motion data (Keogh et al., 2004; Krüger et al., 2010); (Barbič et al., 2004) and (Liu et al., 2005) applied Principal Component Analysis (PCA) to reduce the representation of human motion for motion retrieval, whereas (Chao et al., 2012) used a set of orthonormal spherical harmonic function. Recently, (Deng et al., 2009) and (Wu et al., 2009) clustered motion data on hierarchically structured body segments for indexing and retrieval purposes. Nevertheless, most of the aforementioned approaches have been based on primary human actions, such as body posture and pose changes, regardless of the actor's style, emotion and intentions; the quality of the movement and the required effort have been neglected.

Motion indexing, classification and recognition draws high interest in a variety of disciplines and has been studied in-depth by the computer animation community. Some papers consider the actor's style and emotion; still, rough simplifications in simulation and notation of movement are used, ignoring experiences collected in dance notation over the last century. For instance, (Troje, 2009) has applied PCA on human walking clips to extract the lower-dimensional representations of various emotional states. (Shapiro et al., 2006) and (Min et al., 2010) used style components to separate and synthesise different motions. Recently, (Cimen et al., 2013) analysed human emotions using posture, dynamic and frequency based features, aiming to classify the movements of the character in terms of their affective state. However, most of these works overlooked the experiences gained in motion analysis and movement observation over the last century, such as described in LMA.

The idea of using a choreography notation, kinesiology theory or movement analysis to classify the human motion and segregate humanlike skeletons into different kinematic chains is relatively new. In order to achieve a satisfying simulation for the complex human body language, a simple as possible but complex as necessary description of the human motion is required and LMA (Maletić, 1987) fulfils these demands. The relationship between gesture and posture has been studied in movement theory (Lamb, 1965) and psychology (Nann Winter et al., 1989). The posture is defined as a movement that is consistent throughout the whole body, while gesture as a movement of a particular body part or parts (Lamb, 1965). In that manner, (Luo and Neff, 2012) have recently presented a perceptual study of the relationship between posture and gesture for virtual characters, enabling a wider range of expressive body motion variations. (Chi et al., 2000) presented the EMOTE system, for motion parameterisation and expression, that synthesises gesture based on the Effort and Shape qualities derived from LMA. In addition, different approaches for extracting the LMA components have been proposed. (Zhao and Badler, 2005) designed a neural network for gesture animation that maps from extracted motion features to motion qualities in terms of the LMA Effort factors. (Hartmann et al., 2006) quantify the expressive content of gesture based on a review of the psychology literature, whereas (Torresani et al., 2006) used LMA for learning motion styles. Lately, (Wakayama et al., 2010) and (Okajima et al., 2012) demonstrated the use of a subset of LMA features for motion retrieval, while (Kapadia et al., 2013) proposed a method for searching motions in large databases. (Alaoui et al., 2013) have recently developed the *Chiseling Bodies*, an interactive augmented dance performance, that extracts movement qualities (energy, kick, jump/drop, vericality/height and stillness) and returns a visual feedback.

In this paper, we analyse meaningful expressive features inspired from LMA that can be used to capture the emotional state of the dancer and evaluate their influence in motion; we focus on a set of features that includes the Body, Effort, Shape and Space[2] components, with a view to asses the significance of each feature in motion classification and synthesis. This work differs to the literature since it studies how features that have been considered in movement analysis vary with respect to the emotion of the performer; it aims to find similarities and differences in order to achieve a smooth composition or a discrete classification in animation.

3 DATA ACQUISITION

In this study, we used motion capture data recorded with an 8-cameras PhaseSpace Impulse X2 motion capture system (with capture rate 960Hz). The performer wears a special outfit (mocap suit) that can be observed from the cameras surrounding the site where the character moves. The data were then used for skeletal reconstruction, thus capturing the motion. It is important although to note that many different factors may affect the characteristics of a dance performance; the music rhythm, the song lyrics, the performer's personality and idiosyncrasies, experience, emotional charge, and many others. The emotional and intangible characteristics of human behaviour and motion are subjective and may depend on, in addition to the dancer's skill and experience, momentary feelings, the external environment etc. Some of the most important factors that affect the quality of the motion during the capturing procedure are:

- The mocap suit has markers attached on every limb giving the feeling of restriction or reduced motion to the performer. *Solution:* Allow 5-10 minutes for warming up to familiarise the user with the outfit.
- The size of the laboratory restrict the movements of the performer to a limited space; in addition, the feeling of laboratory environment reduces the user's intimacy with the area, thus limiting his creativity. *Solution:* Dances can be captured in environments which are familiar to the dancer, such as dance schools, thereby reducing the potential influence of external factors.

Five different actors performed in our laboratory, each of them acting six different emotional states. The actors are professional dancers, one male and four females, while their age range between 20 and 35 years old. The dancers were asked to perform an emotional state for 90 - 120 seconds, together with music of their choice; each actor had the required time to prepare the scenario and get ready for the performance. It is important to note that the performers do not know what the assessment criteria are.

In this project we have used the BVH (Biovision Hierarchical Data) format; it consists of two parts where the first section details the hierarchy and initial pose of the skeleton and the second section describes the channel data for each frame, thus the motion section. BVH format maps all the performers to a normalised character with standard height and body shape.

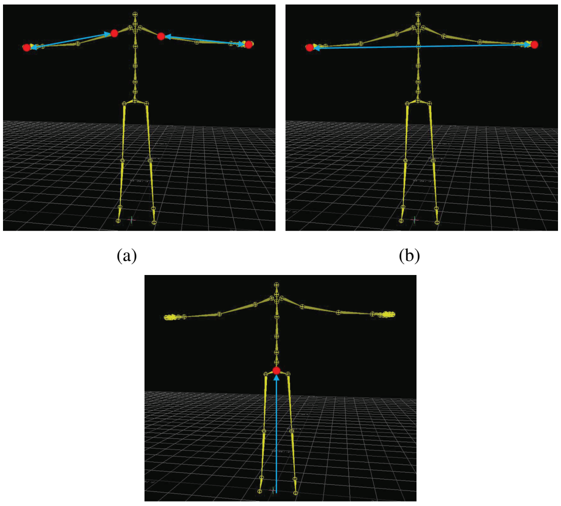
4 MOTION STUDY ANALYSIS

Laban Movement Analysis (LMA) offers a clear documentation of the human motion and it is divided into four main categories: Body, Effort, Shape and Space. In this section, we present the LMA components and the representative features which are indicative to capture the motion properties, allowing users to characterise complex motions and feelings.

4.1 Body Component

Body describes the structural and physical characteristics of the human body in motion. This component is responsible for describing which body parts are moving, which parts are connected, which parts are influenced by others, what is the sequence of the movement between the body parts, and general statements about body organisation. The Body component helps to address the orchestration of the body parts

[2] LMA key terms are capitalised in order to be distinguished from their common English language usage.



(a) (b) (c)

Figure 1: (a) The hands-shoulder displacement, (b) the left hand - right hand displacement, (c) the distance between ground and the root.

and identify the starting point of the movement. In order to express the body connectivity and find the relation between body parts, we propose the following features:

- Displacement and Orientations: Different displacements have been tried such as hand - head, foot - hip etc., but the results were not indicative of any emotion, thus cannot be used for motion indexing. Hands - shoulder and right hand - left hand displacements, as shown in Figure 1(a) and 1(b) respectively, appear to be much more useful for extracting the intention of the performer.
- Hip height can be calculated as the distance between the root joint and the ground, as shown in Figure 1(c). This feature is particularly useful for specifying whether the performer kneels, jumps in the air or falls to the ground.

Other features were studied to extract the Body component, such as the centre of mass, the centroid, the balance, but results showed that they are not offering additional information for the separation of motion.

4.2 Effort Component

Effort describes the intention and the dynamic quality of the movement, the texture, the feeling tone and how the energy is being used on each motion. For example, there is a difference between giving a glass of water to someone from pushing him in terms of the intention of the movement, even if the actual movement is extension of the arm at both cases. Effort in LMA comprises four subcategories - each having two polarities - named *Effort factors*:

1. **Space.** addresses the quality of active attention to the surroundings, *where*. It has two polarities, Direct (when using Direct movement your attention is on a single point in space, focused and specific) and Indirect (giving active attention in more than one thing at once, multi-focused and flexible attention, all around awareness),
2. **Weight.** is a sensing factor, sensing the physical mass and its relationship with the gravity and is related to the movement impact, *what*. The two dimensions of Weight are Strong (bold, forceful, determined intention) and Light (delicate, sensitive, easy intention),
3. **Time.** is the inner attitude of the body toward the time, not the duration of the movement, *when*. Time polarities are Sudden (has a sense of quick, urgent, staccato, unexpected, isolated, surprising) and Sustained (has a quality of stretching the time, legato, leisurely, continuous, lingering),
4. **Flow.** is the continuity of the movement, the base line of “goingness”. It is the key factor in the way that the movement is being expressed because is related with the feelings, and progression, *how*. The Flow dimensions are Bound (is related with the controlled movement, careful and restrained, contained and inward) and Free (is related with released movement, outpouring and fluid, going with the flow).

Effort changes are generally related with the changes of mood or emotion and are essential for the expressivity. The Effort factors can be derived as follows:

Space Feature. Eye focus is a very important factor for understanding the intentions of the performer. Thus, we can extract the intention of the character by studying the attitude and the orientation of the body in relation to the direction of the motion. If the character is moving in the same direction as the head orientation, then the movement is classified as Direct, whereas if the orientation of the head does not coincide with the direction of the motion, then this movement is classified as Indirect. A good approximation of the angle formed between the head and the direction of the movement is given as $\Theta = \theta_1 + \theta_2 + \theta_3$, and combines different angles formed at various key points of the body: the angle between the head and the upper body, θ_1, the angle between the upper and the lower body, θ_2, and the angle between the lower body and the direction of the movement, θ_3. If the direction of the movement is similar (or close to similar, $\Theta \approxeq 0^o$) to the orientation of the head, then the movement is classified as direct, whereas in any other cases is classified as indirect.

Weight Feature. The Weight factor is a sensing factor; it can be estimated by calculating the deceleration of motion and how it varies over time; peaks in decelerations means a movement with Strong Weight, where no peaks (e.g. smooth and fluid) refers to a movement with Light Weight. It is important to note that the Weight factor is velocity independent.

Time Feature. The Time factor can be extracted using the velocity and acceleration features. The velocity of the performer's movement can be estimated by calculating the distance covered by the root joint over a time period (10-frame time windows, note that data are recorded at 30 frames per second). In addition, the average velocity of both hands is calculated, thus adding an extra parameter in movement classification. Using this feature, we can distinguish movements where the performer is standing but his feelings are mainly expressed by the hands.

Flow Feature. A direct way to extract the Flow of each movement is jerk. Jerk is the rate of changes of acceleration or force and it is calculated by taking the derivative of the acceleration of the root joint with respect to time. Bound motion has large discontinuities with high jerk, whereas Free motion has little changes in acceleration.

4.3 Shape Component

While the Body component primarily develops body and body/space connections, Shape analyses the way the body changes shape during movement. There are several subcategories in Shape, such as mode or quality, which describe static shapes that the body takes, the relation of the body to itself, the relations of the body with the environment, the way the body is changing toward some point in space, and the way the torso can change in shape to support movements in the rest of the body.

The Shape of the body at any given time can be captured using the volume of the performer's skeleton. The volume is given by calculating the convex hull of the bounding box given from the five end-effector joints (head, left and right hand, left and right foot), as presented in Figure 2(a). The area within the bounding box was also calculated but the results do not differ significantly from the volume results; volume will be preferred as it gives more distinct values for separation and classification of the performer's emotions.

In addition, the torso height can be used to estimate the distance between the head and the root joint, as shown in Figure 2(b). This feature indicates

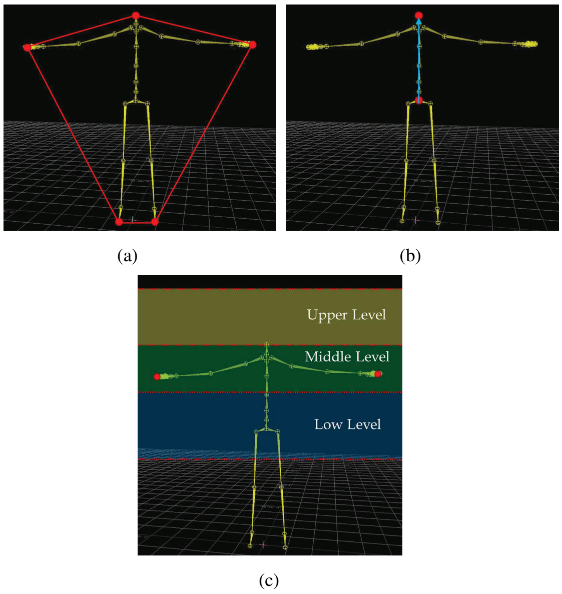


Figure 2: (a) The bounding box, (b) the distance between hip and head (torso), (c) the different levels of the body where hands can be located.

whether the performer is crouching, meaning bending his torso. Please note that this feature does not take into account whether the legs are bent, but only if the torso is kept straight or not.

The Shape component can be also identified using an algorithm for understanding whether the hands of the performer are moving on the upper level of the body, the middle level or the low level (see Figure 2(c)). Any hand movement with orbit above the performer's head is classified as upper level. When the movement is carried out in the space between the head and the midpoint position between the head and root, then it is considered as middle level, where, if the movements are lower than the midpoint position are classified as low level. The same algorithm applies even if the performer is crouching, kneeling or jumping.

4.4 Space Component

Space describes the movement in relation with the environment, spatial patterns, pathways, levels, and lines of spatial tension. It articulates the relationship between the human body and the three-dimensional space. Laban classified principles for the movement orientation based on the *body kinesphere* (the space within reach of the body, mover's own personal movement sphere) and *body dynamosphere* (the space where the body's actions take place, the general space which is an important part of personal style).

In order to measure the space factor, we used two

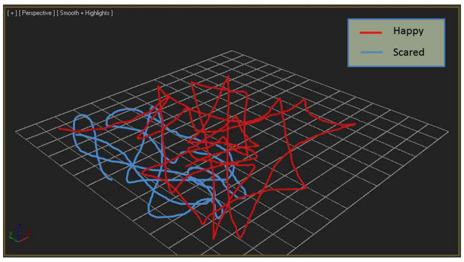


Figure 3: The trajectory of the performer in the allowable space after 15 seconds. In red colour is the trajectory of the performer acting happy, where blue is the trajectory when acting scared.

different features: (a) the total distance covered over a time period; we used for evaluation three different time durations of 30, 15 and 5 seconds, and (b) the area covered for the same time period. Using the area key it is expected to quantify the relationship of the performer's feelings with the environment, and whether his movements are taking advantage of all the allowable space. Figure 3 shows an example with the relation of the performer and the environment, where the trajectory of the performer was projected on the ground for two cases: when asked to act (a) a happy feeling, and (b) fear. Obviously, in case of happiness he moved all over the space, thus covering a large area, where in case of fear, he limited the movements only to a small section of the allowable space.

5 RESULTS

In this section, the experimental results are presented and analysed; our method takes as input raw motion data in BVH format and extracts meaningful features to provide a compact and representative space for indexing. The proposed features are evaluated based on their ability to extract the qualitative and quantitative characteristics of each emotion, how they vary in different emotional states, as well as their importance for valuable motion indexing.

Our datasets comprise BVH files from acted contemporary dance performances of five different dancers. It is important to recall that BVH skeletons are by default normalised, thus skeleton and joint distances, such as arm span and other displacements, are calculated under the same conditions. The size of motion clips range between 90 - 120 seconds; we used different size windows (usually 300-frames windows with a 15-frames step) to draw the proposed LMA features and measure the observations, resulting in 200 observations for each clip (1000 observations for each feeling). Figure 4 shows two different snapshots from our video clips, where actors/dancers perform

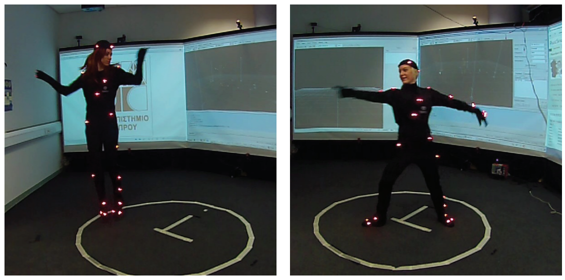


Figure 4: Snapshots of contemporary dance performances at our laboratory.

different contemporary dance scenarios. Six representative feelings or emotional situations (happiness, sadness, curiosity, nervousness, activeness and fear) have been studied for evaluation and comparison purposes.

5.1 Body Features

Displacement and Orientations. Studying the features of displacement and orientation, we were able to understand some of the motion qualities and distinguish different feelings. The distance between hands and hips varies significantly in different feelings; for instance, the average distance when the performer was acting happiness or having an active behaviour was relatively large (53*cm*), with a large distribution in values (standard deviation over 21*cm*). On the other hand, the feelings of sadness, nervousness and fear had an average distance close to 38*cm* and standard deviation up to 16*cm*, where values tend to be concentrated in the range between 28*cm*-32*cm*. Curiosity has an average distance close to 46*cm* and a relatively small deviation; the distance rarely exceeded 80*cm*, which is a valuable criterion to distinguish it from other emotions. Studying the distance between the two hands, we noticed that for happiness, curiosity and activeness, the performer has chosen to make movements with large distance between right and left hand, where in some cases this distance reach up to 140*cm*. The average value is close to 68*cm*, while the standard deviation is 32*cm*. The cases of sadness and fear have a much smaller average distance between hands (42*cm*), where large distances appear rarely. Finally, when the performer impersonated the feeling of nervousness, the average distance is marginally larger than the case of sadness, but smaller than happiness.

Hip Height. Looking at the distance between the skeleton root and the ground, the feeling of happiness has values greater than 90*cm* (the initial distance in BVH files when the character is in standing pose is 90*cm*), indicating that the performer was jumping. In the same way, the distance histogram for active be-

Figure 5: The correlation matrix showing the relation between different emotions with regards to the body features.

haviours resembles the histogram of the happy feeling. In contrast, when the performer asked to act a sad feeling, the distance get values only between $60cm$ to $90cm$, which implies that the performer never jumped. The feeling of nervousness can be distinguished from other feelings since the distance is mainly distributed between the values $85cm$ and $90cm$, having the smallest standard deviation ($3cm$). A clear observation perceived for the curiosity feeling is that there were cases whereas the distance had very low values (close to $30cm$), with large distance distribution (standard deviation near to $13.5cm$). Lastly, the feeling of fear was impersonated with kneeling or even sitting on to the ground (probably to protect the body, leaving a smaller body area unprotected), driving to the lowest value for distance ($24cm$) and the largest standard deviation ($17cm$).

In order to assess the significance of the proposed body features, a correlation matrix is introduced to present the association between the different emotional states. The correlation matrix measures the Pearson's linear correlation coefficient, that is normalised to take values between 0 and 1 (0 - no correlation, 1 - high correlation). Figure 5 gives the correlation between the emotions with regard to the body features; the matrix displays the average correlation over all body features. Clearly, most of the emotions have small correlation coefficients, meaning it is easy to be distinguished; as expected, happiness and fear are correlated, as well as fear and active behaviour.

5.2 Effort Features

Head Orientation and Direction of Movement. The head orientation is proved to be a valuable factor for understanding the effort component; for instance, happiness, nervousness and activeness can be expressed as direct movements since mostly the performer was moving in the same direction of the head. On the other hand, looking at curiosity, we notice that movements are mainly indirect since the performer's direction was independent of the head orientation (the performer moved around the "target" to observe). The head during sadness moved somewhat uncontrollably, without being a remarkable criterion for separation. Similarly, fear had large variations on head orientation, probably because the performer was checking the area to protect himself.

Body Velocity. Studying clips with happy state, we observed that the velocity of the character is relatively high (average speed $72cm/s$), while values close to $90cm/s$ appeared several times. The maximum value for velocity is $165cm/s$ and the standard deviation is $37.5cm/s$. This is consistent with the feeling of happiness, since being happy most of the times means a playful and full of energy behaviour. Curiosity and active states have similar behaviours to happiness, with maximum speed $67.8cm/s$ and $78.9cm/s$, respectively. In contrast, the average speed of the character when impersonated a sad state was significantly smaller ($33cm/s$), with standard deviation close to $24cm/s$, while speed never exceeds $105cm/s$. The cases of nervousness and fear have average velocity $45cm/s$ and $57cm/s$, respectively, but they differ in standard deviation; being scared means large variation ($39cm/s$) compared to nervousness ($28cm/s$).

Body Acceleration. All emotional states have the same acceleration histogram, where its shape has a normal Gaussian distribution. However, each emotion has a different standard deviation; curiosity, activeness and fear have the largest distribution ($4.5cm/s^2$) in motion acceleration, where the largest acceleration for these feelings reach up to $16.5cm/s^2$, meaning that moves were mainly sudden. During the feeling of happiness, even if movements are mainly fast, the acceleration is not very high with maximum value at $12cm/s^2$. In contrast, sadness produce sustained movements with small distribution in acceleration, where the highest value is lower than $9cm/s^2$.

Hands Velocity. The hands velocity feature performs similarly to the body velocity feature; however, it is a useful feature to study since there are cases where feelings are mainly expressed using the hands and not the whole body, amplifying the separation criteria between different emotions. The dissection of each hand's velocity as individual does not provide any additional information, so it is ignored.

Jerk. Jerk is a feature to measure the flow of a movement. As expected, the happy feeling and the active behaviour have high average values for jerk, indicating that movements are mainly bound (maximum value is $5.1cm/s^3$). On the other hand, sadness is mostly represented with free movements. Curiosity, nervousness and fear seems to have similar behaviour with maximum value close to $3.6cm/s^3$.

Volume. Volume is one of the most decidable features for understanding motion; looking at the results, we observe that the performer, in order to demonstrate happiness, tries to increase the body volume by opening and stretching arms and legs. Generally speaking, the feeling of happiness is intentional; the performer, trying to convey or transfer his emotions to others, gets the largest average volume ($0.63m^3$), where in some cases reaches up to $2.4m^3$. Similarly, during his attempt to investigate a subject or the place showing curiosity, he tends to increase the volume by stretching the body for better observation (to come closer to the object), having a maximum volume of $2.3m^3$ (average $0.63m^3$). During an active behaviour, the performer's movement shows energy and action thus, the volume can take different values, from large to small; the average volume is $0.45m^3$, while the maximum value is $1.65m^3$. On the contrary, the performer has chosen a smaller volume (average $0.23m^3$) for the feeling of sadness, because probably he does not want to grab other's attention; the movements are more gathered together, and the value never exceeds $1.1m^3$. Similarly, when the performer acts in nervous the volume remains low (average $0.34m^3$) with a maximum value close to $1.3m^3$. Finally, the feeling of fear tries not to leave any part of the body unprotected or uncovered, resulting in an average volume close to $0.25m^3$, and maximum $1m^3$.

Figure 6 shows the relation between six emotional states regarding to effort. It is evident that the effort features can be a valuable factor for understanding movements, able to extract movement's quality, and they are useful for separating actions.

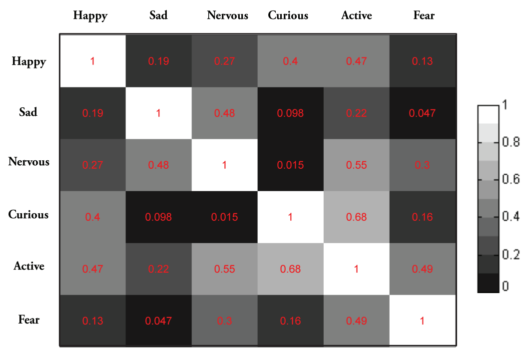


Figure 6: The correlation matrix showing the relation between different emotions with regards to the effort features.

5.3 Shape and Space Features

Hands Level. LMA suggests that hand movement and position could provide reliable principles for understanding the performer's intention and the quality of his movement; thus, this feature will play an important role for the extraction of the performer's emotional state. It is important to note that this feature differs from the body volume, which may increase even when there is a forward extension of the hands. The proposed feature can help in understanding at what level hands are located, i.e. if they are moving over the head or forward. Looking at the data, happiness and curiosity have similar volume shapes; however, when the performer was acting happiness, hands appeared several times in the upper level, in contrast to curiosity where hands rarely moved there. Another clear observation is in case of fear, where hands were mainly located at the middle level, probably protecting the head. Similarly, in case of nervousness or sadness, hands almost never appeared on the upper level. Nevertheless, a combination of this feature with others, such as the body volume and the inter-hands distance, give us additional information about the structure and the quality of the motion.

Space and Total Distance Covered in a 30 Second Window. During acting the emotion of happiness, the performer moved on average $21.5m$; the covered area is large, suggesting that the performer, in a try to externalise his feelings, moved almost in all the available space. Activeness was impersonated with similar behaviour to happiness. Contrary, in case of sadness or fear, the total distance covered is much lower, almost half the case of happiness ($10.5m$), pausing several times. The area covered is small, which implies that our character did not move across the available space but only in few areas; probably the performer did not want to express his feelings or just wanted to protect himself. Looking at the clips of the emotional state of nervousness, the most important observation is that the character never stopped moving, having a permanently fixed speed and therefore a steady increase in the distance covered (total distance covered is $13.5m$). Similarly, the covered area is larger than the case of sadness but smaller than happiness, since the performer moves over the same trajectories or repeat the same actions. Lastly, in curiosity clips we observe that the average distance covered is not very large ($17m$), whereas the area covered is large. This indicates that the performer moved around an object to have a better and more detailed observation.

Torso Height. The distance between the root and the head is also an important factor for the qualitative analysis of the movement, able to separate different emotions. The feelings of happiness and nervousness were expressed with no major changes in torso shape; it has been noticed that the body remained in

Figure 7: The correlation matrix showing the relation between the emotions based on the shape and space features.

Figure 8: The correlation matrix showing the relation between different emotions using all features.

an upright position (62*cm*). Curiosity does not differ from the feeling of happiness; although the performer was usually bending the knees, the body remained stretched continuously. Conversely, when the character depicted the sad feeling, there was a large variation of the distance, with minimum value at 50*cm*. Oddly, when the performer had an active behaviour, the distance distribution resembles the case of sadness; the character performed a wide range of movements, including head and body bending. Fear propels the performer to keep the body in an upright position, mostly because of the need for self-protection, with an average value close to happiness and nervousness.

Figure 7 presents the correlation matrix between emotions based on the shape and space features. Since there are only few features to distinguish the nature of feelings, there are cases with high correlation, such as curiosity - nervousness or happiness - sadness. Nevertheless, it seems to add a valuable criterion for understanding the nuance of the movements, able to separate most of the other emotional states.

5.4 All Features

Finally, the correlation between the emotional states has been tested using all the features discussed in this paper. A matrix showing the normalised Pearson's linear correlation coefficients is illustrated in Figure 8. It is evident that the aforementioned features offer a distinct manner for separating the emotional states. The proposed features were able to identify the difference in the movement quality and structure, based on the LMA components; none correlation coefficient exceeds 0.5, proving that they offer reliable distinguishing conditions for classifying movements.

The results confirm the effectiveness of the proposed features to capture the LMA components, thus extracting the quality and identifying the diversity of each movement. By extracting and studying the qualitative and quantitative characteristics of the movement, we can have a deeper understanding of the performer's emotions and intentions, proving that the emotional state of the character affects the quality of the motion.

6 CONCLUSIONS

We have proposed a method that can automatically extract motion qualities from dance performances, in terms of Laban Movement Analysis, for motion analysis and indexing purposes. We believe that this paper contributes to the understanding of the human behaviour and actions from an entirely different perspective that those currently used in computer animation; it can be used as an alternative or complement to the standard methods of measuring similarity in animation.

Summarising, in this work we studied which features are able to extract the LMA components in a mathematical and analytical way, aiming to capture the movement's nuance. We used acted dance data with different emotional states and studied how the proposed features changed when the performer was acting different feelings. The results confirm that the aforementioned features are indicative to extract the LMA components, implying their importance in motion indexing and classification; the proposed features succeed to characterise each of the movements, forming a valuable criterion for the separation of the performer's emotions. In addition, we investigated the correlations between the performer's acting emotional state and the qualitative and quantitative characteristics of motion. Experiments show that the proposed LMA features and the emotional state of the performer are highly correlated, proving the efficiency of our approach. A limitation of the proposed methodology is that a subset of the features requires the use of a short time-window, resulting in delays in the extraction of the user emotions.

Future work will focus on the study of more emotional states for a better understanding of the quality of human movements and the intentions of the performer. In addition, more performances from different actors will be captured for better evaluation of the results; some captures will take place at dance schools to reduce the potential influences of the laboratory environments. We are also planning to study how the gender, age, weight and height affect the emotion expression and recognition and whether these factors can be correlated with motion and emotional state. Furthermore, we will study the performance of the classifier in relation to the size of the window used for motion clips' segmentation, as well as the weight of influence of each feature in the classification of movements. Besides, the results of this paper will be referred to establish a similarity function that measures the correlation between different actions. In contrast to the existing techniques, we intend to compare every movement based, not only on the position, posture or the rotation of the limbs, but on the motion qualitative and quantitative characteristics, such as the effort and the purpose that has been executed. In addition, the motion graphs (Zhao and Safonova, 2009) that indicate possible future action paths will be enriched, apart from whether a movement is well-matched to another, with the qualitative and quantitative characteristics of the action.

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