DOI: 10.1111/cgf.12598

COMPUTER GRAPHICS *forum*
Volume 34 (2015), number 6 pp. 262–276

Emotion Analysis and Classification: Understanding the Performers' Emotions Using the LMA Entities

Andreas Aristidou[1], Panayiotis Charalambous[1,2] and Yiorgos Chrysanthou[1]

[1]Department of Computer Science, University of Cyprus, Cyprus
a.aristidou@ieee.org, panayiotis77@hotmail.com, yiorgos@cs.ucy.ac.cy
[2]INRIA Rennes - Bretagne Atlantique, France

Abstract

The increasing availability of large motion databases, in addition to advancements in motion synthesis, has made motion indexing and classification essential for better motion composition. However, in order to achieve good connectivity in motion graphs, it is important to understand human behaviour; human movement though is complex and difficult to completely describe. In this paper, we investigate the similarities between various emotional states with regards to the arousal and valence of the Russell's circumplex model. We use a variety of features that encode, in addition to the raw geometry, stylistic characteristics of motion based on Laban Movement Analysis (LMA). Motion capture data from acted dance performances were used for training and classification purposes. The experimental results show that the proposed features can partially extract the LMA components, providing a representative space for indexing and classification of dance movements with regards to the emotion. This work contributes to the understanding of human behaviour and actions, providing insights on how people express emotional states using their body, while the proposed features can be used as complement to the standard motion similarity, synthesis and classification methods.

Keywords: behavioural animation, motion capture, motion analysis, emotion classification

ACM CCS: H.3.1 Content Analysis and Indexing: Indexing methods—; I.3.7 Three-Dimensional Graphics and Realism: Animation

1. Introduction

Motion capture can be defined as a technological process for recording three-dimensional (3D) positioning and orientation information of a moving object with direct applications in many areas including entertainment, sports, medical and military applications, as well as robotics and computer vision. In recent years, the large availability of pre-recorded motion data [Car03, Uni11, Uni12] together with motion synthesis advancements [KGP02, AFO03], enable facile motion composition through indexing and classification. However, in order to achieve good connectivity between different human actions, an understanding of the associated human behaviour is required. Knowledge of human movements including basic actions (e.g. walk, run or jump) and stylistic variations (e.g. intention, expression or gender) is essential for effective motion analysis.

The personality of the character, the emotion and the purpose of the action are pre-requisites for the description and categorization of movements, and can be determined by its *nuance*. According to Muriel Topaz [PD86], the nuance gives the details of movement style in which essence or meaning is encapsulated in the correct execution of the steps. Stylistic characteristics are represented by the nuance of a movement together with the concentration and energy required to perform the action. Understanding the motion quality will help to apprehend the emotion of the performer, providing a representative search space for indexing motions. Based on the principles of movement observation science [MY88], we aim in extracting the emotional description of motion, a subset of the so-called nuance, and use it for motion indexing and classification purposes.

The stylistic variations conveyed through emotions are both difficult to quantify and highly subjective. To overcome these difficulties, we employ studies from affective science that aim to identify the characteristics required for emotional communication, and to differentiate emotions from one another. There are several

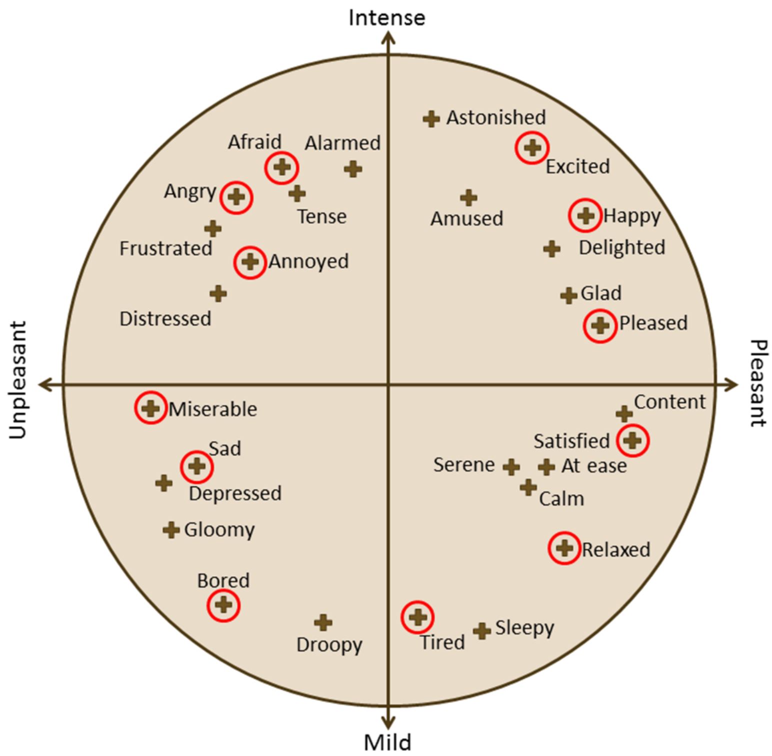

Figure 1: *The Russell's circumplex model of affect: arousal is represented by the vertical axis and valence by the horizontal axis.*

models of emotion or affective state, such as the circumplex model introduced by Russell [Rus80], the emotional diagram proposed by Plutchik [Plu01], the PAD (Pleasure, Arousal, Dominance) emotional state model proposed by Mehrabian [Meh96] and the Lövheim cube model [L11]. In this paper, we use the Russell's circumplex model (RCM) of affect as reference, which distributes emotions in a two-dimensional (2D) circular space, containing arousal and valence axes; Figure 1 shows the RCM and the 12 emotional states used in this work.

In this paper, we propose a framework that can automatically extract motion qualities, in terms of Laban Movement Analysis (LMA) [LU11], aiming to distinguish motions with different emotional states. LMA is a multi-disciplinary system, incorporating contributions from anatomy, kinesiology and psychology that draws on Rudolph 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 used extensively to describe and document dance and choreographies over the last century. Taking into consideration these theories, we analyze the bodily and stylistic characteristics of human motion, so as to investigate the similarities between various emotional states, with regards to the arousal and valence of the RCM, and provide insights on how people express emotional states using their body. The experimental results show that the proposed features can extract the quantitative and qualitative characteristics of dance motion, and can be used to segregate among the emotional states. These LMA features can also be used as complement to the standard similarity, motion classification, indexing and synthesis methods.

2. Literature Review

Motion indexing and classification draws high interest in a variety of disciplines and has been studied in-depth by the computer animation community; a large number of such methods look at the relation between motions, aiming to find logical similarities [KG04, KPZ*04, MRC05, KTWZ10], while others design vocabularies based on a specific content [CLTK11, CLAL12]. Motion has been clustered on hierarchically structured body segments [DGL09, WWX09], while dimensionality reduction methods have been applied to reduce the representation of human motion [BSP*04, LZWM05]. Nevertheless, most of these approaches have been based on primary human actions and its content, regardless of the actor's stylistic variations.

There is a number of techniques that takes into consideration the actor's stylistic variations; for instance, Shapiro *et al.* [SCF06] and Min *et al.* [MLC10] used style components to separate and synthesize different motions. Tournier and Reverel [TR12] proposed a data-driven approach that reduces the dimension pose model based on variational geometric integrators for articulated bodies, and a physically based simulation for real-time character animation. Later, researchers emphasized on individual subsets of motion style, especially in extracting and classifying the emotion of the performer. In this direction, Kshirsagar and Magnenat-Thalmann [KMT02] presented a multi-layer personality model for the design of personality for emotional virtual humans, while Egges *et al.* [EKMT04] described a generic model for updating the parameters related to emotional behaviour. In addition, Gebhard [Geb05] introduced ALMA, a layered model of affect, that simulates emotion, mood and personality affects as they occur in human beings. Many works focused on specific style features [Tro09, RDB*10] to extract lower dimensional representations of various emotional states on human walking clips, while others used a variety of kinematical information, such as velocity, acceleration or jerk for the description of feelings in motion [Wal98]. Kobayashi [Kob08] applied space-temporal features, that were evaluated using higher order singular value decomposition (HOSVD), to examine the relationship between human motion and emotions. Castellano *et al.* [CVC07] presented a methodology to recognize human emotion of four acted emotional states using gesture dynamics, whereas Nicolaou *et al.* [NGP11] used facial expression, shoulder gesture and audio cues to predict emotions in the valence and arousal space. Recently, Cimen *et al.* [CICG13] analyzed human emotions using posture, dynamic and frequency based features, aiming to classify the movements of the character in terms of their affective state. However, rough simplifications in simulation and notation of movement were used, overlooking experiences collected in kinesiology and dance notation over the last century.

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 fulfils these demands. The principles of LMA have been used in computer animation for over a decade; the EMOTE system, introduced by Chi *et al.* [CCZB00], synthesizes gesture, for motion parameterization and expression, based on the LMA effort quality. Later, Zhao and Badler [ZB05] used the EMOTE results to design a neural network for gesture animation. LMA has been successfully used in many applications of computer graphics, such as motion analysis [THB06, LN12] or motion retrieval [WOTO10, OWO12, KCT*13], all with a common denominator the attempt to extract the style of motion. The LMA concept has been also utilized to quantify the expressive content of gestures with regards to the emotion [FSH03, HMP06]. Recently, Truong *et al.* [TBZ15] introduced a set of 3D gesture descriptors based on an LMA model, to recognize the gesture and emotional content of orchestra conductors. In addition, Zacharatos *et al.* [ZGCA13] used a set of body motion features, based on the LMA effort component, to provide sets of classifiers for emotion recognition in a game scenario, Santos and Dias [SD10] presented a tool to describe basic human behaviour patterns using LMA, while others employed a subset of LMA components to explain bodily expressions a human-form robot [NMS02, MKI09, MKI10]. A straight-forward application of Laban theories is dance; Shiratori *et al.* [SNI06] used Laban theory for synthesizing dance motion matched to music, while El Raheb and Ioannides [ERI13] developed a Dance Ontology (DanceOWL) that describes dance moves based on the Labanotation system. Aristidou and Chrysanthou [AC13] used a variety of LMA features to classify acted dance performances with different emotions; the same authors, in [AC14], have provided a brief analysis of how these features change on movements with different emotions, finding movement similarities between the different emotional states.

Currently, an automated model that extracts and measures the LMA entities has not yet been fully implemented. This work advances the current knowledge in motion analysis and emotion classification by proposing a more complete set of bodily and stylistic features that are highly correlated with the LMA components and encode the quantitative and qualitative characteristics of motion. In addition, we study the performer movements to find which features are important in understanding the movement quality and how these features are associated with the emotional state of the performer. We also demonstrate that the proposed LMA features correlate with Russel's circumplex model and help in achieving high classification accuracy compared to other methods.

3. Overview

The study of human behaviour under different emotional states can lead to the creation of virtual characters with different personalities, emotional states or moods. This section presents an overview of a system that characterizes human movement based on the LMA components of motion captured data. The proposed system is divided into two phases, training and classification (Figure 2). During the first phase, six dancers were asked to perform 12 different contemporary dance scenarios, each one with different emotional state. To get the users involved in a more active manner, we used acted dance data of different contemporary scenarios, since movement in dance is the primary way of channeling the feelings to the public. The captured data were segmented and then converted into the Biovision Hierarchical Data (BVH) format. A new classification space is introduced based, not only on the basic description of motion using numerical values, such as joint locations and angles, but on the motion stylistic characteristics (the LMA features). The acted data were then used for training various multi-class classifiers.

On the second phase, data were captured using the same conditions as the training phase. Similarly, the data were processed, and the LMA features were extracted. These data were then classified into the various emotional states using the trained classifiers, showing that the emotional state offers an efficient space for distinguishing actions. In addition, to appraise the significance of the proposed LMA features in motion classification, the importance of each feature in separating the performer's feeling is presented. We have also investigated the correlation between pleasant–unpleasant or intense–mild emotions, and how each feature has been affected based on RCM.

4. The LMA Features

LMA is a language for interpreting, describing, visualizing and depicting all human movements. LMA clearly defines and categorizes human motion into four main components: Body, Effort, Shape and Space. In this section, we discuss the characterization of complex motions and feelings by capturing the motion properties and employing the LMA components and their respective features. The proposed LMA features are calculated to enable motion comparison and classification, with the key joints indicated in Figure 3.

4.1. Body component

The Body component primarily develops body and body/space connections; it describes the structural and physical characteristics of the human body and it 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

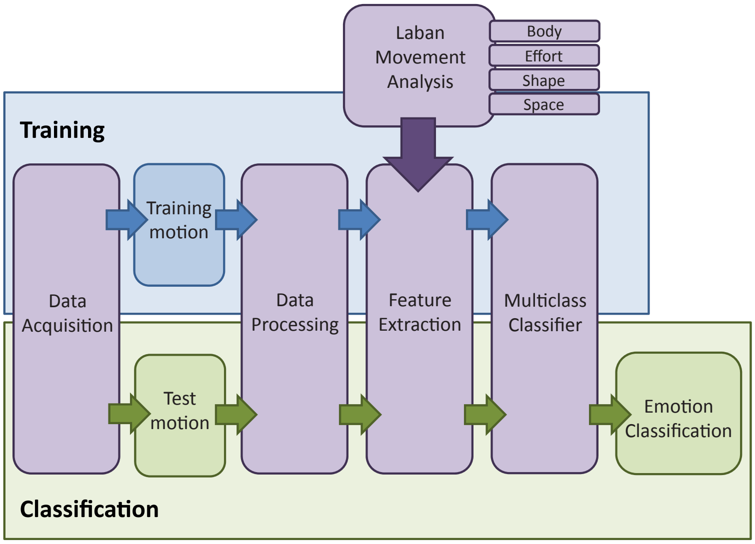

Figure 2: *Overview of the classification system.*

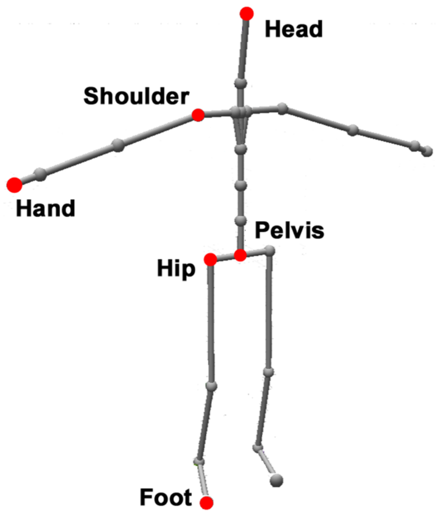

Figure 3: *Representation of the articulated skeletal structure used to calculate the LMA features. Key joints used in the calculations are clearly indicated.*

parts and general statements about body organization. We propose the following features to define the Body component and address the orchestration of the body parts:

- Displacement and orientations: Different displacements, such as feet to hips distance (f_1), hands to shoulders distance (f_2), right hand to left hand distance (f_3) and hands to head distance (f_4) are used to capture the body connectivity and the relation between body parts of the performer.
- Pelvis height (f_5): the distance of the root joint from the ground, in our skeleton the pelvis; this feature is particularly useful for specifying whether the performer kneels, jumps in the air or falls to the ground. In addition, combinations of different displacements (f_6) to recognize specific actions, such as the distance of the hips to the ground, minus the distance of the feet to the hips. This feature provides a metric for relation of the body's posture and the extension of the legs from the body; in that manner, we can differentiate whether the performer lays on the ground with his legs stretched or ducks.
- Centroid: The centroid of the character's body may provide useful information regarding the Body component; factors to be studied are the distance between the ground and the centroid (f_7) and the distance between the centroid and the pelvis (f_8). The actor's centroid shifting can give useful information regarding the style of the actor and can determine the balance of the performer.
- Gait size (f_9): is the distance of the right foot to the left. The size of a human gait may be indicative of motion expression, emotion, style, etc.

Note that all distances involving joints both from the left and right side of the human skeleton ($f_1 - f_4$, f_6) are calculated symmetrically and averaged. For example, (f_1) feet to hips distance is the average Euclidean distance of the left foot to the left hip and the right foot to the right hip, i.e. $f_1 = (\mathrm{d}(L_{\text{foot}}, L_{\text{hip}}) + \mathrm{d}(R_{\text{foot}}, R_{\text{hip}}))/2$. Calculating the average of these distances weights equally the two sides of the body and provides a balanced set of metrics to describe the geometry of the performer's body. It would also be possible to introduce features independently for each side of the body, especially for subvolume motion comparison and motion synthesis approaches.

4.2. Effort component

The Effort component 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; it comprises four subcategories—each having two polarities—named Effort factors:

- **Space**, addresses the quality of active attention to the surroundings. It has two polarities, Direct (focused and specific) and Indirect (multi-focused and flexible attention).
- **Weight**, is a sensing factor, sensing the physical mass and its relationship with the gravity. It is related to the movement impact and has two dimensions: Strong (bold, forceful) and Light (delicate, sensitive).
- **Time**, is the inner attitude of the body towards the time, not the duration of the movement. Time polarities are Sudden (has a sense of urgent, staccato, unexpected, isolated) and Sustained (has a quality of stretching the time, legato, leisurely).
- **Flow**, is the continuity of the movement; it is related with the feelings, and progression. The Flow dimensions are Bound (controlled, careful and restrained movement) and Free (released, outpouring and fluid movement).

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

- Head orientation (f_{10}): The **Space** factor can be derived 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. To this end, we calculate the angle between the head's orientation and the body path of the performer which is expressed by the trajectory of the root joint.
- Deceleration of motion (f_{11}): The **Weight** factor can be identified by studying how the deceleration of motion varies over time; f_{11} is estimated by calculating the deceleration of the root joint. Peaks in decelerations means a movement with Strong Weight, while no peaks refers to a movement with Light Weight; note that **Weight** is velocity independent.
- Movement velocity: The velocity of the performer's movement is indicative of the **Time** factor. It is estimated by calculating the distance covered by the root joint over a time period (f_{12}). In addition, the average velocity of both hands (f_{13}) and both feet (f_{14}) is calculated, so as to distinguish dance movements where the performer remains at the same position, while the choreography is mainly expressed by changes in body postures.
- Movement acceleration ($f_{15} - f_{17}$): The acceleration is another feature for determining the **Time** factor; it is computed by taking the derivative of the aforementioned movement velocities with respect to time; with f_{15} the hips' acceleration, f_{16} the hands' acceleration and f_{17} the feet acceleration.
- Jerk (f_{18}): A 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 (f_{15}) with respect to time. Bound motion has large discontinuities with high jerk, whereas Free motion has little changes in acceleration.

4.3. Shape component

SHAPE analyzes the way the body changes shape during movement; it describes the static shapes that the body takes, the relation of the body to itself, the relation of the body with the environment, the way the body is changing towards some point in space, and the way the torso can change in shape to support movements in the rest of the body. SHAPE can be captured using the following features:

- Volume: The volume of the performer's skeleton (f_{19}) is given by calculating the bounding volume of all joints. In addition, the bodily volume of the performer is subdivided into four subvolumes: upper body (f_{20}), lower body (f_{21}), left side (f_{22}), right side (f_{23}).
- Torso height (f_{24}): The distance between the head and root joints indicates whether the performer is crouching, meaning bending his torso; it does not take into account whether the legs are bent, but only if the torso is kept straight or not.
- Hands level (f_{25}): The relation of the hands' position with regards to the body, indicating whether they are moving on the upper level of the body (over the head), the middle level (between the head and the chest) or the low level (below the chest). The hands' orbit level is calculated even if the performer is crouching, kneeling or jumping.

4.4. Space component

SPACE describes the movement in relation with the environment, pathways and lines of spatial tension. Laban classified the principles for the movement orientation based on the *body kinesphere* (the space within reach of the body, mover's own personal sphere) and *body dynamosphere* (the space where the body's actions take place, the general space which is an important part of personal style). SPACE factor can be derived using two different features:

- Distance (f_{26}): The distance covered over time, which is measured as the length of the projection of the root joint's trajectory to the ground. This prevents vertical translation, e.g. jumping, from mistakenly considered as space coverage by the performer.
- Area (f_{27}): The total area covered over a time period, which is calculated as the area of the polygon formed by the projection of the root joint to the ground.

The SPACE features are expected to quantify the relationship of the performer's feelings with the environment, and whether the performer's movements are taking advantage of all the allowable space. A clear example would be to compare the trajectory of a performer who dances a scenario that expresses happiness or fear. In the first case, the dancer moves all over the space, in contrast with the case of fear where the movements are more cautious and limited only to a small section of the allowable space.

A subset of the proposed LMA features has been successfully used for motion evaluation [ASC14b] within a dance teaching simulator, and for searching motion clips within a motion database [ASC14a].

5. Motion Classification

The proposed LMA features can be used to encode information with regards to the emotion of the performer, taking into consideration both the body and style variations of the performance. The proposed framework takes as input raw motion data in BVH format and extracts meaningful features to provide a compact and representative

Table 1: *The measurements used in our implementation.*

f_s	Description	max	min	mean	std	#
		Measurement				
f_1	Feet–hip distance	ϕ_1	ϕ_2	ϕ_3	ϕ_4	
f_2	Hands–shoulder distance	ϕ_5	ϕ_6	ϕ_7	ϕ_8	
f_3	Hands distance	ϕ_9	ϕ_{10}	ϕ_{11}	ϕ_{12}	
f_4	Hands–head distance	ϕ_{13}	ϕ_{14}	ϕ_{15}	ϕ_{16}	
f_5	Pelvis height	ϕ_{17}	ϕ_{18}	ϕ_{19}	ϕ_{20}	
f_6	Hip-ground minus feet-hip	ϕ_{21}	ϕ_{21}	ϕ_{23}	ϕ_{24}	
f_7	Centroid height	ϕ_{25}	ϕ_{26}	ϕ_{27}	ϕ_{28}	
f_8	Centroid–pelvis distance	ϕ_{29}	ϕ_{30}	ϕ_{31}	ϕ_{32}	
f_9	Gait size	ϕ_{33}	ϕ_{34}	ϕ_{35}	ϕ_{36}	
f_{10}	Head orientation	ϕ_{37}	ϕ_{38}	ϕ_{39}		
f_{11}	Deceleration peaks					ϕ_{40}
f_{12}	Hip velocity	ϕ_{41}	ϕ_{42}		ϕ_{43}	
f_{13}	Hands velocity	ϕ_{44}	ϕ_{45}		ϕ_{46}	
f_{14}	Feet velocity	ϕ_{47}	ϕ_{48}		ϕ_{49}	
f_{15}	Hip acceleration	ϕ_{50}			ϕ_{51}	
f_{16}	Hands acceleration	ϕ_{52}			ϕ_{53}	
f_{17}	Feet acceleration	ϕ_{54}			ϕ_{55}	
f_{18}	Jerk	ϕ_{56}			ϕ_{57}	
f_{19}	Volume	ϕ_{58}	ϕ_{59}	ϕ_{60}	ϕ_{61}	
f_{20}	Volume (upper body)	ϕ_{62}	ϕ_{63}	ϕ_{64}	ϕ_{65}	
f_{21}	Volume (lower body)	ϕ_{66}	ϕ_{67}	ϕ_{68}	ϕ_{69}	
f_{22}	Volume (left side)	ϕ_{70}	ϕ_{71}	ϕ_{72}	ϕ_{73}	
f_{23}	Volume (right side)	ϕ_{74}	ϕ_{75}	ϕ_{76}	ϕ_{77}	
f_{24}	Torso height	ϕ_{78}	ϕ_{79}	ϕ_{80}	ϕ_{81}	
f_{25}	Hands level					ϕ_{82}–ϕ_{84}
f_{26}	Total distance					ϕ_{85}
f_{27}	Total area					ϕ_{86}

space for emotion indexing; the features are evaluated based on their ability to extract the quantitative and qualitative characteristics of each emotion. Empirical findings show that using a 45-frames sliding window with a 15-frame step (our motion data are sampled at 30 fps), can efficiently draw the proposed LMA features (f_i) and measure the observations; smaller time windows do not allow satisfactory computation of the LMA features, whereas too large time windows allow noise and time delays. Overlapping windows were used so that for each 15-frame clip of the initial motion, three separate predictions are made with a majority vote indicating the final emotion. A variety of feature measurements were calculated for each of the f_i, such as the maximum, the minimum, the mean and the standard deviation, resulting in 86 different feature measurements (ϕ_i). These feature measurements are summarized in Table 1.

In order to classify motion clips into affective states, we trained a multi-class classifier using data generated using the proposed LMA features. In this work, we have utilized three of the most popular methodologies used in a multi-class classification context:

- **Random Forests (RF):** proposed by Breiman [Bre01] is an ensemble method for classification and regression where a set of decision trees is learned based on different subsets of the features. Being an ensemble method, each example is classified based on the *mode* of the classes output by all the decision trees. Note that the *mode* of some data is the most frequent value. One important property of this method is that the importance of each feature for classification can be easily calculated.
- **Extremely Randomized Trees (ET):** is similar to the RF method but takes randomization a bit further by randomizing the threshold selection for tree splits aiming to reduce the variance of the model with a slight increase in bias [GEW06].
- **Support Vector Machines (SVM)**: is one of the most widely used classification methods [CV95]. The main idea behind SVMs is constructing maximum-margin hyperplanes to discriminate data samples between different classes.

During pre-processing and before training the classifiers, data that could be considered as noise were removed; for example dancers in different clips would stop for a few seconds or stand still (i.e. very similar data would belong to vastly different classes). In addition, hyperparameters of the classifiers (such as maximum tree depth) were found using grid search, whereas features were normalized to have zero mean and unit length variance. Finally, 10-fold cross validation was used to measure all of the classifiers' accuracy.

In addition to the methods described above, we have experimented with other classification methods, such as K-Nearest Neighbours (KNN) and Naive Bayes (Gaussian and Bernoulli) but classification results were inferior to the ones obtained by the previously mentioned methods and are not presented here. We have also employed principal component analysis (PCA) to project the data into an orthogonal lower dimensional space based on each feature's variance; classification accuracy was reduced with negligible performance gains therefore we would not give any further analysis of these results.

6. Experimental Results

In this section, the classification results are presented and the relation between the affective states are discussed. It is important to note that it is difficult to accurately extract the movement emotions, especially for different performers, since emotional states are subjective and each performer acts differently to different emotional stimuli.

6.1. Data acquisition

Before showing the experimental results, it is important to mention the data acquisition conditions. In our experiments, we used motion capture data recorded in our laboratory with an eight-camera PhaseSpace Impulse X2 motion capture system (with capture rate up to 960 Hz). 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, and indexed in a dance library, similarly to [SAS*12]; data acquisition problems, such as missing data due to marker occlusions, were dealt using state-of-the-art methods [AL13]. It is important though 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 stylistic 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. In addition, ethnographic and cross-cultural studies of emotions have shown the variety of ways in which emotions differ with cultures; cultural differences have been observed in the way in which emotions are valued, expressed and regulated. Thus, we have tried to reduce the potential influence of external factors that affect the quality of the motion during the capturing procedure. For instance, the mocap suit has markers attached on every limb giving the feeling of restriction or reduced motion to the performer. Moreover, the size of the laboratory restricts 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. Thus, we allowed the performers 5–10 min for warming up to familiarize with the outfit and the environment.

Six different actors performed in our laboratory, each of them acting 12 different emotional states, three from each quadrant of RCM (as shown in Figure 1). The actors are professional dancers, one male and five females, while their age ranges between 16 and 35-year olds. Two of the dancers have theatrical, two ballet, whereas the other two have gymnastic backgrounds. The dancers were asked to perform an emotional state for 90–120 s, together with music of their choice; each actor had the required time to prepare the scenario and get ready for the performance. In total, we end up with 72 dances, with approximately 130 min (234 000 frames) of motion; the data set is sufficiently large, having in mind that in the experiments we do not use individual dance moves, but the entire choreography, where the performer dances for 2 min without repeating his/her movements. It is important to note that the performers do not know what the assessment criteria are.

The BVH format has been used for data storage; to enable uniform processing of all acquired motion capture data, we retarget motion to a normalized 3D character with standard height and body shape, so as to evaluate motion under similar circumstances.

6.2. Pearson Correlation Matrix (PCM)

In order to evaluate the performance of the proposed features and check whether they are able to extract the qualitative characteristics of the movement, we have calculated the Pearson's correlation coefficients (PCCs) for each pair of emotions. The PCMs are extracted for each dancer separately; PCCs take values in the $[-1, 1]$ range with values near 1 or -1 indicating high correlation and values near 0 indicating no correlation. Figure 4 shows the correlation matrix that measures the absolute values of the PCCs between each pair of the emotions.

It can be observed that emotions are clustered based on the quadrant of the RCM to which they belong. For instance, *excited*, *happy* and *pleased* are highly correlated, whereas the correlation between *excited* and *happy* is 94%, *happy* and *pleased* is 84%, *excited* and *pleased* is 73%. This observation also applies to other quadrants, some in a higher degree (*bored*, *sad*, *miserable*), while others in a milder degree (*satisfied*, *relaxed*, *tired*). The correlation coefficients in Figure 4 also present the correlation between pleasant and unpleasant emotions, as well as intense and mild emotions. Looking at the results, it can be seen that *happy* is highly correlated to *excited*, *pleased* and *satisfied*, as expected, but is also correlated to *annoyed* and *angry*. This happens since these emotions have similar intensity, as is confirmed by RCM. Another good example is *miserable*, which is an emotion of medium intensity but very unpleasant. *Miserable* is highly correlated to mild and unpleasant emotions, is medium correlated to mild and pleasant, as well as intense and unpleasant emotions, while is uncorrelated to intense and pleasant emotions. It is important to note that PCMs overall have similar trends for all the performers.

6.3. Emotion classification

Figure 5 shows both linear and non-linear 2D representations of the training data for one of the dancers. Similar projections are observed for the other dancers also; each person expresses emotions differently but the relative relationships between the quadrants remain. We can observe the correlation of the mapping with the RCM (see Figure 1). Note that Russell employed MDS to generate the RCM. These 2D projections were obtained by applying the Isomap [TDSL00], Multidimensional scaling (MDS) [Kru64] and randomized PCA (rPCA) [HMT11] methods. These methods seek to find good projections of the data based on different criteria; the Isomap method projects the data using the geodesic distances between the samples, MDS aims in keeping distances from high to lower dimensional spaces and finally PCA projects the data based on their variance. We note that Isomap and MDS are non-linear contrary to PCA.

In this example, we used four emotions, one from each quadrant of RCM. Blue squares represent emotions in the pleasant-intense quadrant, magenta stars express emotions in the pleasant–mild quadrant, green circles reflect emotions in the unpleasant–mild quadrant and red triangles stand for emotions in the unpleasant–intense quadrant. The correlation between our results and the RCM is a strong evidence which indicates that our methodology can apprehend an important amount of LMA components.

6.3.1. *Classification results*

The ability of the proposed features to capture an amount of LMA components is also evaluated by utilizing a multi-class classifier to segregate the emotion of a dance performer. As discussed in Section 5, we have used a variety of different classifiers. Here we show results for RF, ET and SVM. The classification occurs on a two-step process, training, and testing. During training, we provide the features to the classifiers along with labels indicating the emotional state. In addition to the classification algorithms, different strategies were also used; in this work, we have used the well-known One-vs-Rest (OvR) and One-vs-One (OvO) strategies [Bis06]. OvR trains a single classifier per class with the samples of that class as positive samples and all other samples as negatives. On the other hand, OvO trains 66 binary classifiers ($K(K-1)/2$ where $K = 12$), for each possible pair of classes in the training data. At prediction time, a voting scheme is applied: all classifiers are applied to an unseen sample and the class that got the highest number of '+1' predictions gets predicted by the combined classifier.

Figure 6 presents the confusion matrix for six different experimental conditions. The values on the diagonal represents the correct classification rates, while the remaining values shows the

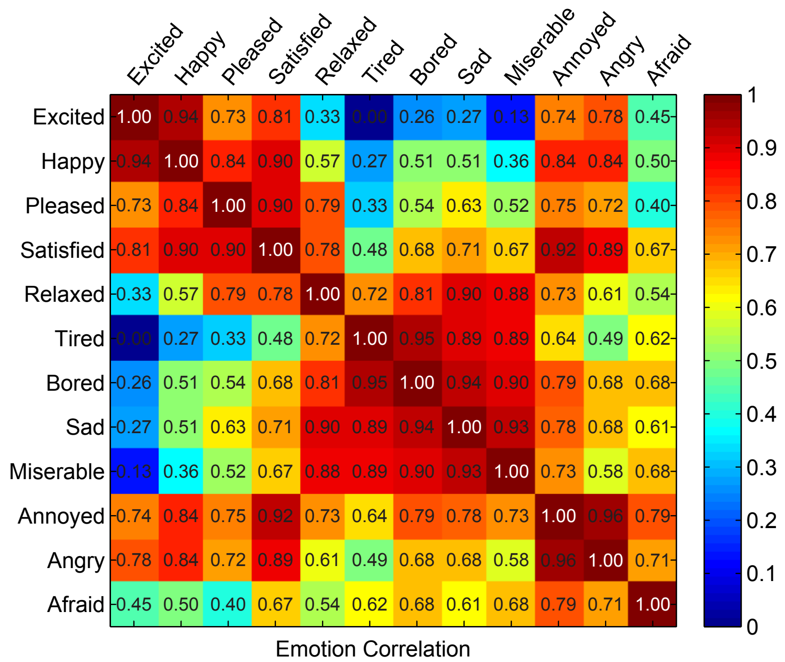

Figure 4: *The Pearson's correlation coefficients, showing the correlation between the 12 emotional states. 0 (blue) indicates no correlation, where 1 (red) high correlation.*

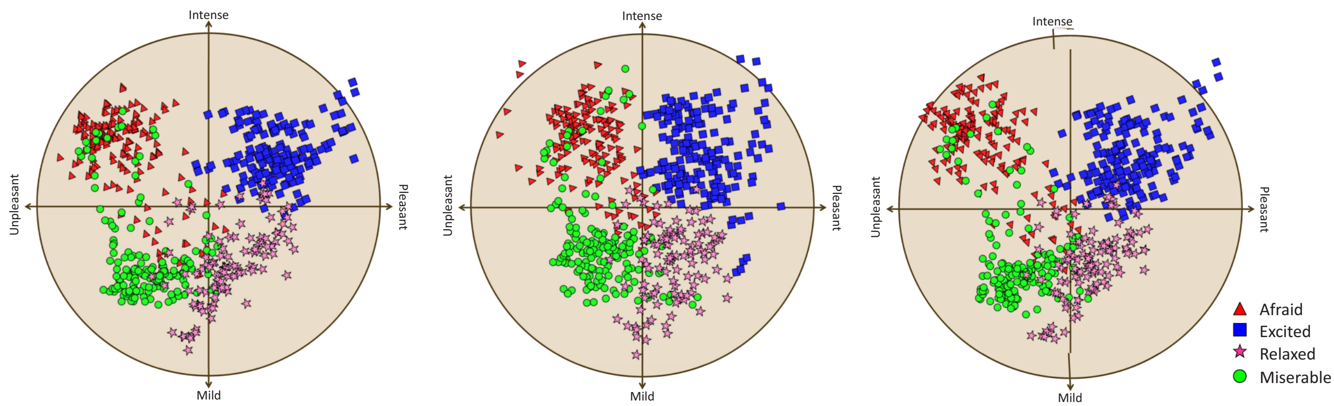

Figure 5: *2D representations of four emotions belonging to different quadrants of the Russell's circumplex model. (a) Ihe Isomap representation, (b) the MDS representation and (c) the rPCA representation. It is clearly observed that emotions are positioned similarly to Russell's circumplex model.*

confusion of a clip with a specific emotion that was wrongly classified to another. For instance, in the case of the RF classifier using the OvR strategy, *annoyed* was correctly recognized on 86% of the data, while it was incorrectly classified as *angry* by 3%, *excited* and *satisfied* by 2%, *relaxed*, *pleased*, *happy*, *bored* and *angry* by 1%. As expected, *annoyed* in some instances has been confused as *angry* or in a more limited scale as other emotions that have close amount of intention or pleasant.

The performance of the classifiers was evaluated by calculating the following measures (Table 2): *Recall* (R), the proportion of motion segments of specific emotion which have been identified by the correct emotion, *Precision* (P) the proportion of the data classified as a specific emotion, whose true class label was indeed that emotion and *Accuracy* (A) the overall proportion of data classified correctly. The measures R, P, A are given by: $R = TP/(TP+FN)$, $P = TP/(TP+FP)$, $A = (TP+TN)/(TP+TN+FP+FN)$, where TP is a true positive, TN is a true negative, FP is a false positive and FN is a false negative prediction. Studying the results of Table 2, we have observed that RF returns the best classification rate, using the OvR strategy. RF achieve recall equal to 84.87%, precision 98.37%

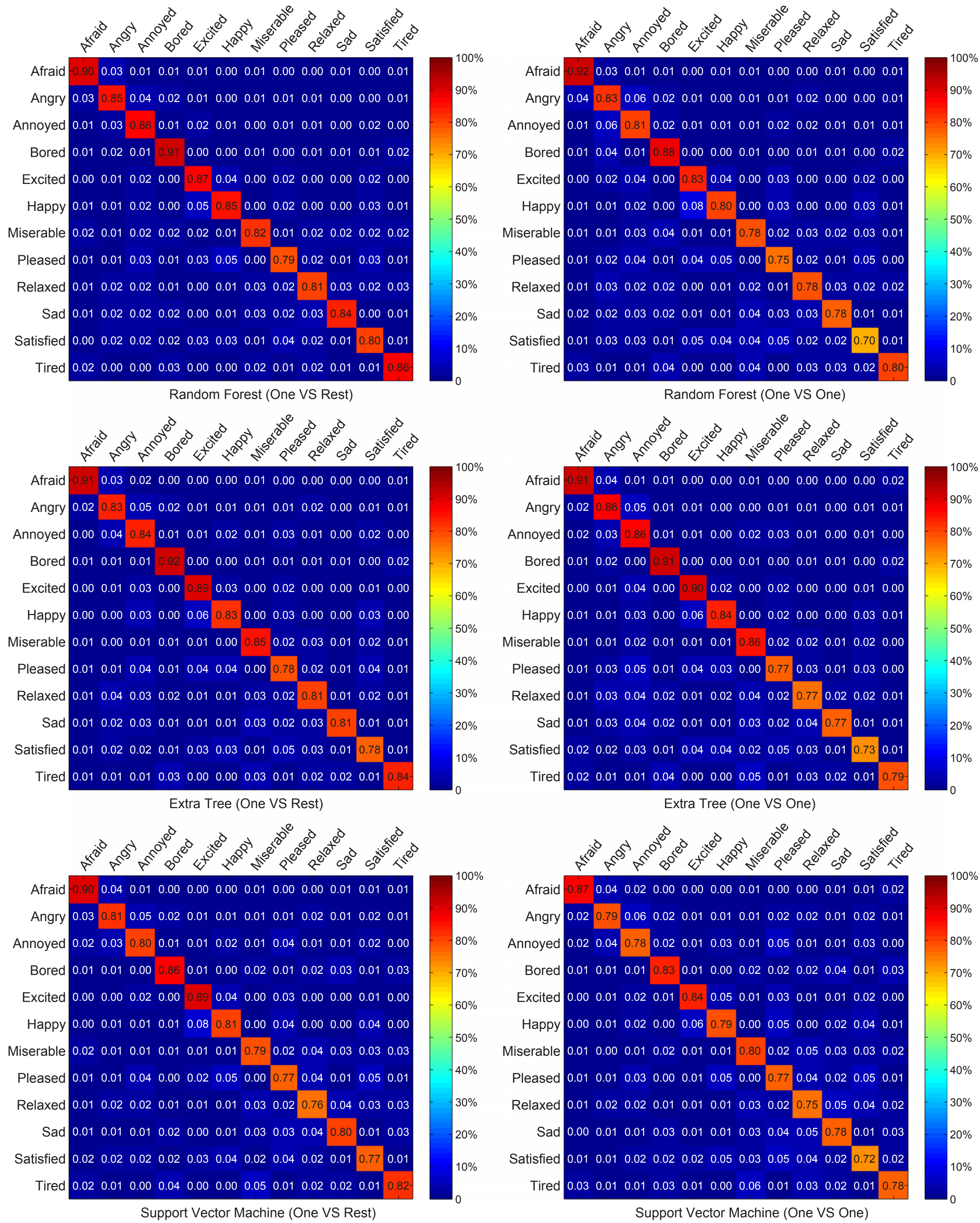

Figure 6: *The confusion matrices of the emotion classification using six case scenarios. On the left side are the confusion matrices using the RF, ET and SVM classifiers, respectively, with the OvR strategy, whereas on the right side are the confusion matrices of the RF, ET and SVM classifiers using the OvO strategy.*

Table 2: *The classification results.*

	One vs Rest								
	RF			ET			SVM		
Emotion	R	P	A	R	P	A	R	P	A
Afraid	90.24	98.72	94.54	91.13	99.07	95.14	90.21	98.56	94.46
Angry	85.50	98.27	92.00	83.50	97.84	90.84	81.37	98.12	89.94
Annoyed	86.29	97.80	92.18	93.88	97.12	90.76	80.42	97.99	89.41
Bored	91.47	98.56	95.09	91.59	98.70	95.21	86.07	98.44	92.38
Excited	87.40	98.19	92.92	89.32	98.15	93.74	89.21	98.06	93.73
Happy	85.33	98.20	91.89	82.59	98.26	90.59	80.87	97.87	89.60
Miserable	82.25	98.58	90.55	85.30	98.27	91.93	79.37	97.89	88.84
Pleased	79.05	98.09	88.79	78.44	97.41	88.27	76.85	96.97	87.31
Relaxed	80.92	98.33	89.79	80.96	98.07	89.73	76.39	97.52	87.23
Sad	83.76	98.78	91.38	80.79	99.14	99.07	79.95	98.04	89.19
Satisfied	80.04	98.22	89.32	78.09	97.99	88.27	76.72	97.34	87.34
Tired	86.24	98.66	92.55	84.09	98.80	91.55	81.68	98.11	90.07
Total	**84.87**	**98.37**	**91.75**	**84.14**	**98.23**	**91.35**	**81.59**	**97.91**	**89.96**
	One vs One								
Afraid	91.84	98.42	95.19	91.02	98.68	94.91	87.25	98.77	93.09
Angry	82.79	97.12	90.17	86.19	97.65	92.06	78.80	98.04	88.64
Annoyed	81.21	96.63	89.22	86.10	96.64	91.58	78.09	97.25	88.00
Bored	88.24	98.07	93.28	91.18	98.64	94.98	83.41	98.10	90.95
Excited	83.41	97.66	90.75	90.34	98.05	94.29	84.15	98.26	91.34
Happy	80.16	97.95	89.26	83.53	98.53	91.15	78.50	97.60	88.33
Miserable	78.43	97.72	88.34	85.76	98.03	92.05	80.01	97.63	89.05
Pleased	75.33	97.22	86.70	76.97	97.53	87.59	77.31	96.37	87.24
Relaxed	78.44	98.01	88.44	76.56	97.88	87.47	75.39	96.93	86.52
Sad	77.56	98.44	88.19	77.48	99.03	88.38	77.73	97.29	87.81
Satisfied	70.07	97.35	84.13	72.99	98.20	85.87	72.19	96.63	84.89
Tired	79.83	98.73	89.41	79.04	98.72	89.02	78.04	98.01	88.25
Total	**80.61**	**97.78**	**89.42**	**83.10**	**98.13**	**90.78**	**79.24**	**97.57**	**88.68**

and accuracy 91.75%. The *Bored* emotion returns the highest classification accuracy, 95.09%, while *pleased* the lowest, 88.79%. See Table 2 for a more detailed representation of the classifiers used in this study.

Studying these results, we notice some important observations. For instance, the more intense or mild an emotion is, the greater the success in classification; the classification accuracy for the *excited* clips, which is the most intense feeling of the pleasant-intense quadrant, is 92.92%, while as we move towards the midline of RCM it decreases (*pleased* rate is 88.79%). The same applies to all quadrants. In addition, different classification accuracy is achieved for performers with different backgrounds; the classification accuracy is higher for dancers with theatrical background, achieving on average 94.75% accuracy, compared to 89.77% when the dancers have ballet background or 90.59% when they have gymnastic.

The performance of the classifiers was also tested using sliding windows of different sizes; we have noticed that classification results were almost the same when smaller (yet large enough to get satisfactory measurements) or larger windows were used. Finally, we performed classification using lower dimensional representations of the data using PCA; we noticed marginal performance gains to decreased classification quality (61.5%, 93.8% and 77.4% recall, precision and accuracy, respectively) and therefore dimensionality reduction is not used by default in the current version of the system.

6.3.2. *Feature importance*

The classification accuracy or the average error rate is not a criterion for deciding which of the features are better when used in combination with the others; features should be evaluated on their ability to provide a representative space for indexing. For this purpose, we calculate the feature importance to select the most significant features that are indicative of certain emotions. To measure the feature importance, we employ the randomized tree–based methods (RF and ET) which build sets of decision trees based on different subsets of the features. This way, a natural score for the importance of each feature can be deduced by the gain/loss in classification if some features are included or not.

Figure 7 list the features regarding their importance in separating the emotional state of the performer using the RF (top) and Extremely Randomized Tree classifiers (bottom); the percentage value for each feature (f_i) is calculated as the average importance of the

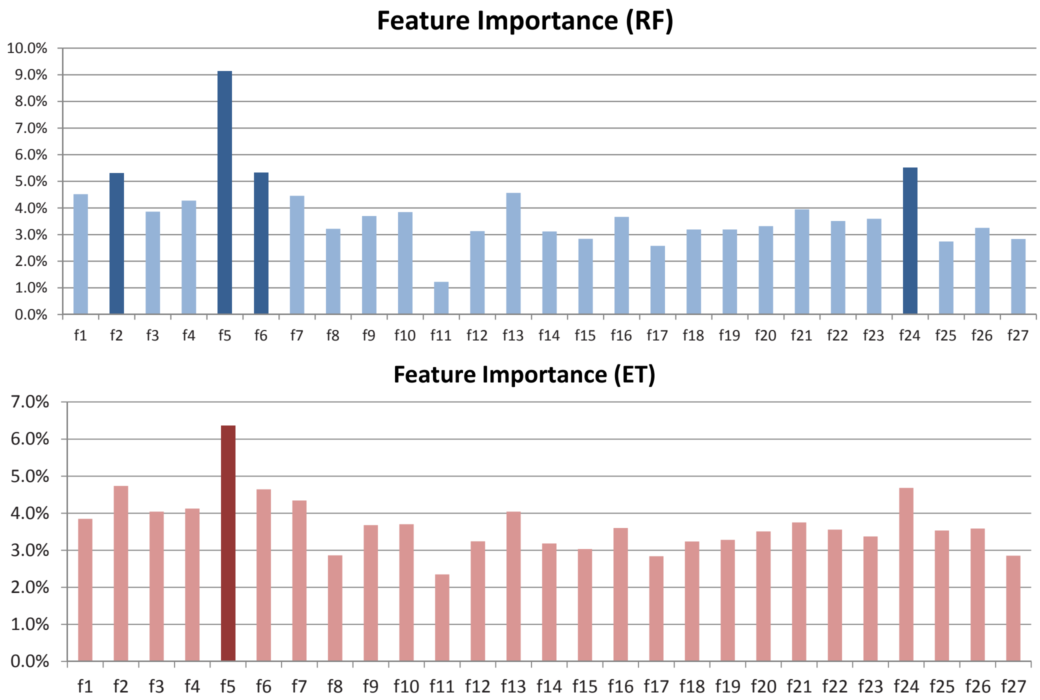

Figure 7: *The importance of the 27 proposed features for the classification of the emotions; features with more than 5% weight of impact are highlighted. The upper diagram shows the importance of the features when Random Forests (RF) were used, while the lower shows the importance for the case of Extremely Randomized Trees (ET).*

feature measurements (ϕ_i) which represent that feature for all the performers. Results show that f_5 and f_{24} are the dominant features for classifying feelings. More specifically, the dominant feature f_5 that indicates whether the performer kneels or jumps seems to be an important factor for the categorization of the performer's affective state. Nevertheless, results show that all features contribute to the extraction of the qualitative and quantitative characteristics, some to a greater while other to a lesser extent. Data show little importance for f_{11}, f_{17} and f_{27}, thus these features contribute less to the classification.

In order to evaluate the significance of the proposed features, in a different manner, we trained the RF classifier utilizing a subset of the proposed features, similar to the ones in [CICG13]. The classification accuracy was reduced to 82.3%, while the recall and precision were decreased to 69.1% and 95.2%, respectively).

6.3.3. *Classifying new data*

Finally, in order to test the reliability of the proposed classification framework, we asked from each dancer to prepare a choreography whereas four different emotional states interchange, one emotion from each quadrant of the RCM; the RF classifier was trained using the separated dance performances with the 12 emotions.

Note that there is an overlap in the decision windows, where for every 15 frames we have three decisions (45-frame windows with 15-frame step); thus, there are instances where the decision is not solid. In such cases, we decide the emotion of the respective segment using a majority vote strategy. In case there is no majority in the votes, the window is classified as *undetermined*. Figure 8 shows the results, in real time, of a dance performance where the performer changed emotional states starting with *excited*, then *relaxed*, *miserable* and ending with *angry*. Colours on the bottom bar indicate the accuracy of the classifier. Dark green indicates correct prediction, light green states that the predicted class falls in the same quadrant as the original class, yellow indicates cases where the window could not be classified to any of the 12 states and finally red means misclassification to a different quadrant.

We can observe a short delay in the recognition of the emotional state because of the majority vote; in addition, the use of sliding windows for extracting the features that define the LMA components results in delays on the adjustment of the system.

Experimental results verify the validity of the approach, proving that the aforementioned features offer a reliable space for movement classification with regards to the performer's sentiments. Looking at the results in Figure 8, we can observe that most of the time the classification is correct or at least falls into the same quadrant as the correct class. There is a period at the beginning of the capture where the dancer is starting the performance and deciding what to do where classification failed, but overall complete misclassification is rare.

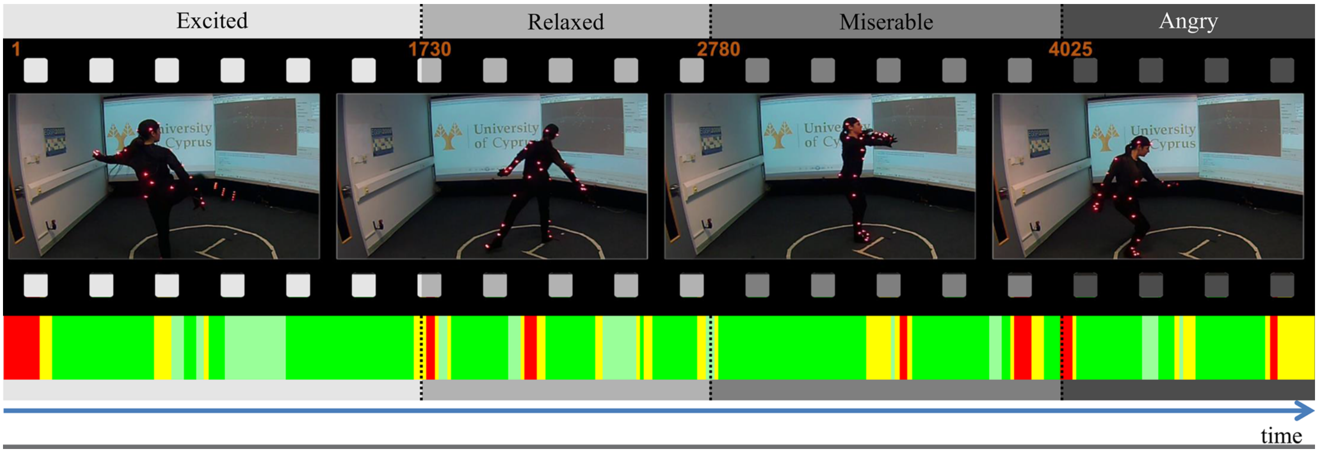

Figure 8: *The classification accuracy of our methodology when dancers asked to perform a choreography where four different emotions interchange; green colour indicates that the emotion at that specific time window is classified correctly, light green means that the emotion belongs to the same quadrant, yellow is undetermined and red is wrongly classified.*

7. Conclusions and Future Work

In this work, we have proposed a framework that uses a variety of features to encode characteristics of motion using LMA. This paper contributes to the understanding of the human behaviour and actions, while the proposed features can be used as alternative and/or complement to the standard similarity and motion classification methods. We have shown that the proposed features are indicative to capture an amount of the LMA elements, which fully or partially encodes the so-called motion nuance. 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. The proposed features can be used so as to evaluate dance performances, for dance comparison, and teaching simulators, while the outcomes can be used to synthesize movements taking into consideration not only the geometry of the pose but also the qualitative characteristics of the motion. In addition, it can be used for the creation of virtual characters with different behaviours and personalities, or creating situations where the character alternates different sentiments.

We used acted dance data with 12 different emotional states to derive the importance of each of the proposed features for the classification of motion. Using a variety of different classifiers, including RF, ET and SVM, we evaluated the performance of the proposed features in capturing the so-called movement's nuance. The presented experimental results confirm that the aforementioned features are indicative to extract the LMA components, implying their importance in motion indexing and classification. These feature measurements offer a distinct manner for separating the emotional states, identifying the difference in the movement quality and structure, thus forming a valuable criterion for the separation of the performer's emotions; the average classification accuracy is 91.75%, proving that they offer reliable distinguishing conditions for classifying movements and offering new guidelines for human motion synthesis. Finally, we have proved that the performer's acting emotional state and the motion quality based on LMA are highly correlated.

Our immediate future target is capturing more performances from different actors, while captures will take place at dance schools to reduce the potential influences of the laboratory environments. We are also planning to study how other factors may affect the emotion expression and recognition, such as the gender, age, weight and height, and whether these factors can be correlated with the emotional state; a user study will also be conducted to support the findings of our work. Furthermore, we aim to explore the influence of the nuance in many other different aspects, such as the composition of partial-body movements for the creation of new movements (where the stylistic characteristics will be taken into consideration), the prediction and/or connection of possible future movements, motion comparison and evaluation purposes.

Acknowledgements

This work (DIDAKTOR/0311/73) is cofinanced by the European Regional Development Fund and the Republic of Cyprus through the Research Promotion Foundation. The authors would also like to thank all the dancers who participated in the experiments.

References

[AC13] Aristidou, A., Chrysanthou Y.: Motion indexing of different emotional states using LMA components. In *SA '13: SIGGRAPH Asia 2013 Technical Briefs* (NY, USA, 2013), ACM, pp. 21:1–21:4.

[AC14] Aristidou A., Chrysanthou Y.: Feature extraction for human motion indexing of acted dance performances. In *GRAPP '14: Proceedings of the International Conference on Computer Graphics Theory and Applications* (Lisbon, Portugal, 2014), pp. 277–287.

[AFO03] Arikan O., Forsyth D. A., O'Brien J. F.: Motion synthesis from annotations. *ACM Transactions on Graphics 22*, 3 (2003), 402–408.

[AL13] Aristidou A., Lasenby J.: Real-time marker prediction and CoR estimation in optical motion capture. *The Visual Computer 29*, 1 (2013), 7–26.

[ASC14a] Aristidou A., Stavrakis E., Chrysanthou P.: LMA-based motion retrieval for folk dance cultural heritage. In *Proceedings of 5th International Conference on Progress in Cultural Heritage Preservation* (Limassol, Cyprus, 2014), LNCS, Springer, pp. 207–216.

[ASC14b] Aristidou A., Stavrakis E., Chrysanthou P.: Motion analysis for folk dance evaluation. In *EG GCH' 14: Proceedings of EG Workshop on Graphics and Cultural Heritage* (Darmstadt, Germany, 2014), Eurographics, pp. 55–64.

[Bis06] Bishop C. M.: *Pattern Recognition and Machine Learning (Information Science and Statistics)*. Springer-Verlag New York, Inc., Secaucus, NJ, USA, 2006.

[Bre01] Breiman L.: Random Forests. *Machine Learning 45*, 1 (2001), 5–32.

[BSP*04] Barbič J., Safonova A., Pan J.-Y., Faloutsos C., Hodgins J. K., Pollard N. S.: Segmenting motion capture data into distinct behaviors. In *GI'04: Proceedings of the Graphics Interface Conference* (London, Ontario, Canada, May 2004), pp. 185–194.

[Car03] Carnegie Mellon University: MoCap Database: http://mocap.cs.cmu.edu/, 2003. Accessed 22 January 2015.

[CCZB00] Chi D., Costa M., Zhao L., Badler N.: The emote model for effort and shape. In *Proceedings of SIGGRAPH '00* (NY, USA, 2000), ACM, pp. 173–182.

[CICG13] Cimen G., Ilhan H., Capin T., Gurcay H.: Classification of human motion based on affective state descriptors. *Computer Animation & Virtual Worlds 24*, 3-4 (2013), 355–363.

[CLAL12] Chao M.-W., Lin C.-H., Assa J., Lee T.-Y.: Human motion retrieval from hand-drawn sketch. *IEEE Transactions on Visualization and Computer Graphics 18*, 5 (2012), 729–740.

[CLTK11] Chan J. C. P., Leung H., Tang J. K. T., Komura T.: A virtual reality dance training system using motion capture technology. *IEEE Transactions on Learning Technologies 4*, 2 (2011), 187–195.

[CV95] Cortes C., Vapnik V.: Support-vector networks. *Machine Learning 20*, 3 (1995), 273–297.

[CVC07] Castellano G., Villalba S., Camurri A.: Recognising human emotions from body movement and gesture dynamics. In *Affective Computing and Intelligent Interaction*, Vol. *4738* of LNCS (Springer-Verlag, Berlin, Heidelberg, Germany 2007), pp. 71–82.

[DGL09] Deng Z., Gu Q., Li Q.: Perceptually consistent example-based human motion retrieval. In *I3D '09: Proceedings of the ACM Symposium on Interactive 3D Graphics and Games* (Boston, Massachusetts, USA, 2009), ACM, pp. 191–198.

[EKMT04] Egges A., Kshirsagar S., Magnenat-Thalmann N.: Generic personality and emotion simulation for conversational agents. *Computer Animation & Virtual Worlds 15*, 1 (2004), 1–13.

[ERI13] El Raheb K., Ioannidis Y.: Dance in the world of data and objects. In *Proceedings of the International Conference in IT for Performing Arts, Media Access, and Entertainment*, Vol. *7990* of LNCS (Porto, Portugal, 2013) Springer, pp. 192–204.

[FSH03] Fagerberg P., Ståhl A., Höök K.: Designing gestures for affective input: An analysis of shape, effort and valance. In *MUM '03: Proceedings of the 2nd International Conference on Mobile and Ubiquitous Multimedia* (Norrköping, Sweden, 2003), pp. 57–65.

[Geb05] Gebhard P.: ALMA: A layered model of affect. In *AAMAS '05: Proceedings of the Fourth International Joint Conference on Autonomous Agents and Multiagent Systems* (NY, USA, 2005), ACM, pp. 29–36.

[GEW06] Geurts P., Ernst D., Wehenkel L.: Extremely randomized trees. *Machine Learning 63*, 1 (2006), 3–42.

[HMP06] Hartmann B., Mancini M., Pelachaud C.: Implementing expressive gesture synthesis for embodied conversational agents. In *GW '05: Proceedings of the 6th International Gesture Workshop* (2006), Springer-Verlag, pp. 188–199.

[HMT11] Halko N., Martinsson P.-G., Tropp J. A.: Finding structure with randomness: Probabilistic algorithms for constructing approximate matrix decompositions. *SIAM Review 53*, 2 (2011), 217–288.

[KCT*13] Kapadia M., Chiang I.-k., Thomas T., Badler N. I., Kider Jr., J. T.: Efficient motion retrieval in large motion databases. In *I3D '13: Proceedings of the ACM Symposium on Interactive 3D Graphics and Games* (Orlando, Florida, USA, 2013), ACM, pp. 19–28.

[KG04] Kovar L., Gleicher M.: Automated extraction and parameterization of motions in large data sets. *ACM Transactions on Graphics 23*, 3 (2004), 559–568.

[KGP02] Kovar L., Gleicher M., Pighin F.: Motion graphs. *ACM Transactions on Graphics 21*, 3 (2002), 473–482.

[KMT02] Kshirsagar S., Magnenat-Thalmann N.: A multilayer personality model. In *SMARTGRAPH '02: Proceedings of the 2nd International Symposium on Smart Graphics* (NY, USA, 2002), ACM, pp. 107–115.

[Kob08] Kobayashi Y.: The emotion sign: Human motion analysis classifying specific emotion. *Journal of Computers 3*, 9 (September 2008), 20–28.

[KPZ*04] Keogh E., Palpanas T., Zordan V. B., Gunopulos D., Cardle M.: Indexing large human-motion databases. In *VLDB '04: Proceedings of the Thirtieth International Conference on Very Large Data Bases* (Toronto, Canada, 2004), Vol. *30*, pp. 780–791.

[Kru64] Kruskal J. B.: Multidimensional scaling by optimizing goodness of fit to a nonmetric hypothesis. *Psychometrika 29*, 1 (1964), 1–27.

[KTWZ10] Krüger B., Tautges J., Weber A., Zinke A.: Fast local and global similarity searches in large motion capture databases. In *SCA'10: Proceedings of the ACM SIGGRAPH/Eurographics Symposium on Computer Animation* (Madrid, Spain, 2010), pp. 1–10.

[Lö11] Lövheim H.: A new three-dimensional model for emotions and monoamine neurotransmitters. *Med Hypotheses 78*, 2 (December 2011), 341–349.

[LN12] Luo P., Neff M.: A perceptual study of the relationship between posture and gesture for virtual characters. In *MIG '12: Proceedings of Motion in Games* (Rennes, France, 2012), Springer, pp. 254–265.

[LU11] Laban R., Ullmann L.: *The Mastery of Movement* (4th edition). Dance Books Ltd., Binsted, Hampshire, UK, 2011.

[LZWM05] Liu G., Zhang J., Wang W., McMillan L.: A system for analyzing and indexing human-motion databases. In *SIGMOD '05: Proceedings of the International Conference on Management of Data* (New York, NY, USA, 2005), pp. 924–926.

[Meh96] Mehrabian A.: Pleasure-arousal-dominance: A general framework for describing and measuring individual diff. in temperament. *Current Psychology 14*, 4 (1996), 261–292.

[MKI09] Masuda M., Kato S., Itoh H.: Emotion detection from body motion of human form robot based on Laban Movement Analysis. In *Principles of Practice in Multi-Agent Systems*, Vol. *5925* of LNCS. Springer-Verlag, Berlin, Heidelberg, Germany (Nagoya, Japan, 2009), pp. 322–334.

[MKI10] Masuda M., Kato S., Itoh H.: Laban-based motion rendering for emotional expression of human form robots. In *Knowledge Management and Acquisition for Smart Systems and Services*, Vol. *6232* of LNCS, Springer-Verlag, Berlin, Heidelberg, Germany (Daegue, Korea, 2010), pp. 49–60.

[MLC10] Min J., Liu H., Chai J.: Synthesis and editing of personalized stylistic human motion. In *I3D '10: Proceedings of the ACM Symposium on Interactive 3D Graphics and Games* (Washington, D.C., USA, 2010), ACM, pp. 39–46.

[MRC05] Müller M., Röder T., Clausen M.: Efficient content-based retrieval of motion capture data. *ACM Transactions on Graphics 24*, 3 (2005), 677–685.

[MY88] Moore C.-L., Yamamoto K.: *Beyond Words: Movement Observation and Analysis*, No. v. 2. Gordon and Breach Science Publishers, United Kingdom, 1988.

[NGP11] Nicolaou M., Gunes H., Pantic M.: Continuous prediction of spontaneous affect from multiple cues and modalities in valence-arousal space. *IEEE Transactions on Affective Computing 2*, 2 (April 2011), 92–105.

[NMS02] Nakata T., Mori T., Sato T.: Analysis of impression of robot bodily expression. *Journal of Robotics and Mechatronics 14*, 1 (2002), 27–36.

[OWO12] Okajima S., Wakayama Y., Okada Y.: Human motion retrieval system based on LMA features using IEC method. In *Innovations in Intelligent Machines* (Springer-Verlag, Berlin, Heidelberg, Germany, 2012), Studies in Computational Intelligence, vol. 376, pp. 117–130.

[PD86] Preston-Dunlop V.: *Dance Words*. Harwood Academic Publishers, Amsterdam, The Netherlands, 1986.

[Plu01] Plutchik R.: The nature of emotions. *American Scientist 89*, 4 (April 2001), 344–350.

[RDB*10] Romeo M., Dematei M., Bonequi J., Evans A., Blat J.: A reusable model for emotional biped walk-cycle animation with implicit retargeting. In *AMDO '10: Proceedings of the 6th International Conference on Articulated Motion and Deformable Objects* (Mallorca, Spain, 2010), Springer-Verlag, pp. 270–279.

[Rus80] Russell J. A.: A circumplex model of affect. *Journal of Personality and Social Psychology 39* (1980), 1161–1178.

[SAS*12] Stavrakis E., Aristidou A., Savva M., Loizidou Himona S., Chrysanthou Y.: Digitization of cypriot folk dances. In *Proceedings of 4th International Conference on Progress in Cultural Heritage Preservation (EuroMed 2012)* (Limassol, Cyprus, 2012), vol. *7616*, LNCS, pp. 404–413.

[SCF06] Shapiro A., Cao Y., Faloutsos P.: Style components. In *GI '06: Proceedings of the Graphics Interface Conference* (Canada, 2006), pp. 33–39.

[SD10] Santos L., Dias J.: Laban Movement Analysis toward behavior patterns. In Emerging Trends in Technological Innovation, Vol. *314* of *Advances in Information and Communication Technology*. (Springer-Verlag, Berlin, Heidelberg, Germany 2010), pp. 187–194.

[SNI06] Shiratori T., Nakazawa A., Ikeuchi K.: Dancing-to-music character animation. *Computer Graphics Forum 25*, 3 (September 2006), 449–458.

[TBZ15] Truong A., Boujut H., Zaharia T.: Laban descriptors for gesture recognition and emotional analysis. *The Visual Computer* (2015), 1–16.

[TDSL00] Tenenbaum J. B., DeSilva V., Langford J. C.: A global geometric framework for nonlinear dimensionality reduction. *Science 290*, 5500 (2000), 2319–2323.

[THB06] Torresani L., Hackney P., Bregler C.: Learning motion style synthesis from perceptual observations. In *NIPS '06: Proceedings of the Conference in Neural Information Processing Systems* (Vancouver, British Columbia, Canada, 2006), Vol. *19*, pp. 1393–1400.

[TR12] Tournier M., Reveret L.: Principal geodesic dynamics. In *SCA '12: Proceedings of the ACM SIGGRAPH/Eurographics*

Symposium on Computer Animation (Aire-la-Ville, Switzerland, 2012), Eurographics Association, pp. 235–244.

[Tro09] TROJE N. F.: Decomposing biological motion: A framework for analysis and synthesis of motion gait patterns. *Journal of Motion 2*, 5 (2009), 371–387.

[Uni11] University of Texas at Arlington: Human Motion DB: http://smile.uta.edu/hmd/, 2011. Accessed 22 January 2015.

[Uni12] University of Cyprus: Dance MoCap Database: http://dancedb.cs.ucy.ac.cy/, 2012. Accessed 22 January 2015.

[Wal98] WALLBOTT H. G.: Bodily expression of emotion. *European Journal of Social Psychology 28*, 6 (1998), 879–896.

[WOTO10] WAKAYAMA Y., OKAJIMA S., TAKANO S., OKADA Y.: IEC-based motion retrieval system using Laban Movement Analysis. In *KES'10: Proceedings of the 14th International Conference on Knowledge-Based and Intelligent Information and Engineering Systems: Part IV* (Cardiff, UK, 2010), pp. 251–260.

[WWX09] WU S., WANG Z., XIA S.: Indexing and retrieval of human motion data by a hierarchical tree. In *VRST '09: Proceedings of the 16th ACM Symposium on Virtual Reality Software and Technology* (Kyoto, Japan, 2009), ACM, pp. 207–214.

[ZB05] ZHAO L., BADLER N. I.: Acquiring and validating motion qualities from live limb gestures. *Graphical Models 67*, 1 (2005), 1–16.

[ZGCA13] ZACHARATOS H., GATZOULIS C., CHRYSANTHOU Y., ARISTIDOU A.: Emotion recognition for exergames using Laban Movement Analysis. In *MIG '13: Proceedings of Motion in Games* (Dublin, Ireland, 2013), Springer, pp. 39–44.

Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's web site:

Video S1.