Motion indexing of different emotional states using LMA components

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Abstract

Recently, there has been an increasing use of pre-recorded motion capture data, making motion indexing and classification essential for animating virtual characters and synthesising different actions. In this paper, we use a variety of features that encode characteristics of motion using the Body, Effort, Shape and Space components of Laban Movement Analysis (LMA), to explore the motion quality from acted dance performances. Using Principal Component Analysis (PCA), we evaluate the importance of the proposed features - with regards to their ability to separate the performer's emotional state - indicating the weight of each feature in motion classification. PCA has been also used for dimensionality reduction, laying the foundation for the qualitative and quantitative classification of movements based on their LMA characteristics. Early results show that the proposed features provide a representative space for indexing and classification of dance movements with regards to the emotion, which can be used for synthesis and composition purposes.

CR Categories: H.3.1 [Content Analysis and Indexing]: Indexing methods—; I.2.10 [Vision and Scene Understanding]: Motion—; I.3.7 [Three-Dimensional Graphics and Realism]: Animation—;

Keywords: motion capture, Laban Movement Analysis, motion indexing, emotional states

1 Introduction

Motion capture - a technology used for turning the observations of a moving subject into 3D position and orientation information - has contributed to the sharp increase in use of pre-recorded motion. The increasing availability of large motion databases (CMU 2003; UTA 2011; UCY 2012), in addition to advancements in motion synthesis (Kovar et al. 2002; Arikan et al. 2003), have made motion indexing and classification essential for easy motion composition. However, in order to achieve good connectivity between different human actions, it is important to understand the human behaviour. Motion analysis consists of understanding different types of human movements, such as basic human actions (e.g. walking, running, or jumping) and stylistic variations (e.g. emotion, intention, expression, or gender). The stylistic variations though, are difficult to measure; the movement of the human body is complex and it is not possible to completely describe the human action if rough simplifications in motion description are used and motion has not been properly indexed from the outset. In order to extract motion qualities, we present an analytical approach that uses Laban Movement Analysis (LMA) (Maletić 1987); LMA is a multidisciplinary 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.

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In this paper, we propose a mathematical framework that can automatically extract motion qualities, in terms of LMA entities, aiming to distinguish motions with different emotional states. To get the users involved in a more active manner, we used acted dance data of different contemporary scenarios, since movement is the primary way of channeling the feelings to the public. We aim to appraise the significance of the proposed features in motion classification using Principal Component Analysis (PCA), where the weight of each feature in separating the performer's feeling is presented. A new classification space is introduced based, not only on the basic description of motion such as the posture, but on the motion qualitative and quantitative characteristics. PCA has been also used for dimensionality reduction, resulting in a less complex system; the reduced segments (principal components) are used as input to a Support Vector Machine (SVM) classifier, which decides about the segment with respect to emotion. Results demonstrate the efficiency of the proposed features in motion indexing and classification of different emotional states.

2 Related Work

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 methods has been developed over the last decade; some papers in the literature classify motions using simple vocabularies (such as walk, run, kick, box) (Kovar and Gleicher 2004), while others design vocabularies based on a specific subject (e.g. kickboxing, dancing) (Chan et al. 2011). A content-based retrieval method was introduced by (Müller et al. 2005) to compute a small set of geometric properties for motion similarity purposes. Different techniques have been proposed for spatial indexing of motion data (Keogh et al. 2004; Krüger et al. 2010). Recently, (Deng et al. 2009) and (Wu et al. 2009) clustered motion on hierarchically structured body segments, whereas (Chao et al. 2012) used a set of orthonormal spherical harmonic function. In addition, (Barbič et al. 2004) and (Liu et al. 2005) applied PCA to reduce the representation of human motion for motion retrieval. Nevertheless, most of these approaches have been based on primary human actions, regardless of the actor's stylistic variations.

Lately, motion analysis was studied taking into consideration the actor's stylistic variations; for instance, (Shapiro et al. 2006) and (Min et al. 2010) used style components to separate and synthesise different motions, while (Troje 2009) has applied PCA on human walking clips to extract the lower-dimensional representations of various emotional states. Recently, (Cimen et al. 2013) analyse 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, ignoring experiences collected in 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 (Guest 2005) fulfils these demands. The EMOTE system (Chi et al. 2000) synthesises gesture, for motion parameterisation and expression, based on the LMA effort quality; then, (Zhao and Badler 2005) used the EMOTE results to design a neural network for gesture animation. A user-centered approach for incorporating affective expressions in interactive applications based on effort, shape and emotional state was presented by (Fagerberg et al. 2003), whereas (Luo and Neff 2012) studied the relationship between posture and gesture for virtual characters. Finally, (Okajima et al. 2012) used a subset of LMA features for motion retrieval, while (Kapadia et al. 2013) proposed a method for searching motions in large databases.

In this brief, we propose to study the problem of dimension reduction and classification for large collection of mocap data using LMA qualities, combining the emotional states with the LMA characteristics, in order to improve the motion recognition rate.

3 Motion Analysis

Laban Movement Analysis (LMA) is a language for interpreting, describing, visualising and notating all ways of human movement. LMA offers a clear documentation of the human motion and it is divided into four main categories: Body, Effort, Shape and Space[1]. In this section, we present the LMA components and the representative features which capture the motion properties, allowing users to characterise complex motions and feelings.

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

- Displacement and Orientations (f_1): Different displacements, such as (i) feet - hips, (ii) hands - shoulder, and (iii) right hand - left hand distances, are used to capture the body connectivity and the relation between body parts of the performer.
- Hip height (f_2): the distance between the root joint and the ground; this feature is useful for specifying whether the performer kneels, jumps in the air or falls to the ground.
- Gait size (f_3): The size of a human gait may also be indicative for motion expression, emotion, style etc.

3.2 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_4): 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.
- Deceleration of motion (f_5): The Weight factor can be identified by studying how the deceleration of motion varies over time. Peaks in decelerations means a movement with Strong Weight, where no peaks refers to a movement with Light Weight; note that Weight is velocity independent.
- Movement velocity (f_6): 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. In addition, the average velocity of both hands is calculated; using this feature, we may, for instance, distinguish movements where the performer is standing but his feelings are mainly expressed by the hands.
- Movement acceleration (f_7): The acceleration is another feature for determining the Time factor; it is computed by taking the derivative of the movement velocity with respect to time.
- Jerk (f_8): Jerk is used to extract the Flow of each movement; it is the rate of changes of acceleration or force and it is calculated by taking the derivative of the acceleration with respect to time. Bound motion has large discontinuities with high jerk, whereas Free motion has little changes in acceleration.

3.3 Shape component

Shape analyses 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 toward 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 (f_9): The volume of the performer's skeleton is given by calculating the convex hull of the bounding box given from the five end-effector joints (head, hands and feet).
- Torso height (f_{10}): The distance between the head and the root joint; it 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_{11}): 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 (lower the chest). The hands orbit level is calculated even if the performer is crouching, kneeling or jumping.

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

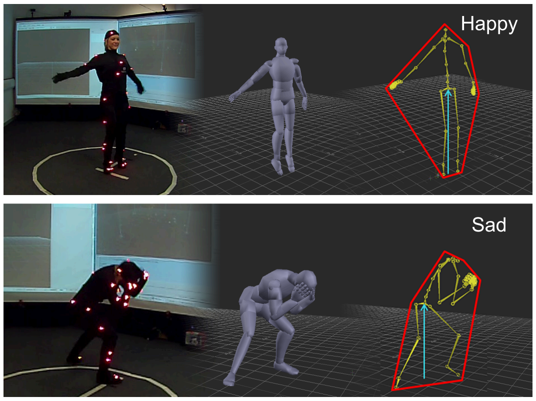

Figure 1: *Snapshots of contemporary dance performances captured at our laboratory (left) with the relative skeletons (centre), and a depiction of f_2 and f_9 (right).*

3.4 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_{12}): The distance covered over a time period, and
- Area (f_{13}): The area covered over a time period.

Combining f_{12} and f_{13}, 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.

4 Experimental Results

Our datasets comprise of BVH files from contemporary dance performances of five different dancers, acting six representative feelings or emotional situations (happiness, sadness, curiosity, nervousness, activeness and fear). The performances were captured in our laboratory using PhaseSpace Impulse X2 mocap system and they were segmented into 30 second clips (900 frames), giving a database with over 80 clips, at least 10 clips for each feeling. We used different size windows (usually 150 or 300 frame-windows with a 15-frames step) to draw the proposed LMA features and measure the observations, resulting in 40 observations for each clip (400 observations for each feeling). A variety of feature measurements were calculated for each of the f_is, such as the maximum, the minimum, the mean and the standard deviation, resulting in 45 different feature measurements. It is important to note that different factors may affect the characteristics of a dance performance; the music rhythm, the song lyrics, the performer's personality, 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. In order to ensure the reliability of the data, the performers do not know what the assessment criteria are. Figure 1 shows two different snapshots from our video clips, where actors/dancers perform contemporary dances with different emotional states.

Features are evaluated on their ability to provide a representative space for indexing; thus, we performed PCA to select the most significant features that are indicative of certain emotions. Table 1 lists the features regarding their importance in separating the emotional state of the performer; the percentage value for each feature is based on the PCA coefficients of their feature measurements. 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.

Table 1: *The significance of features for motion classification.*

LMA features							
f_9	f_6	f_1	f_7	f_8	f_3	f_{12}	f_5
10.3%	10.1%	9.8%	9.5%	8.7%	8.5%	8.2%	7.7%
f_{11}	f_4	f_{10}	f_2	f_{13}			
7.4%	7.3%	5.3%	3.8%	3.4%			
Principal Components							
F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8
47.4%	11.8%	9.2%	8.9%	5.4%	3.7%	2.7%	2.0%
F_9	F_{10}	...					
1.7%	1.3%	...					

Nevertheless, the large number of the feature measurements makes the classification problem complex, thus we need to obtain a transformation that offers easy description of data. PCA can reduce the dimensions of the classification space, finding the lower dimensional space spanned by the observations. PCA is generating a new set of principal components (F_i), each is a linear transformation from the original feature measurements. Table 1 lists the indices of the dominant eigenvectors (new features); observing the results, it is obvious that the first ten principal components offer more than 94% information gain, despite the dimensionality reduction.

The classification efficiency of the proposed features and their ability to capture the LMA components are evaluated by utilising an SVM classifier with linear kernel; the classification takes into consideration the capability of separating the emotional status of the performer and it occurs on a two-step process, training, and testing. During training we provide the features to the classifier along with labels indicating the emotional state; thereafter, SVM returns a number of support vectors that are used for testing. Since there are only six emotional classes, we use the one-against-rest strategy for multi-class classification. 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. We experiment two main categories: (a) when we use data from the same performer, but at different times, for both training and testing purposes, we have 100% classification success, (b) when data from different performers are used for training and testing respectively, the classification accuracy is 95.6%.

The results confirm the effectiveness of the proposed features to extract the quality and identify the diversity of each movement; we have shown that these features are indicative to capture an amount of the LMA characteristics, while using PCA, they can be encoded to only ten principal components. 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.

5 Conclusion

We have proposed a method that can automatically extract motion qualities from dance performances, in terms of Laban Movement Analysis. We used acted dance data with different emotional states to derive the importance (weights) of each of the proposed features for the classification of motion. In addition, using PCA, we produced a lower-dimensional space for human motion indexing, thus reducing classification's complexity. Using an SVM classifier, we evaluated the performance of the proposed approach, where outcomes verify the validity of our method to classify movements with regards to the acting emotional state. The presented experimental results confirm that the aforementioned features are indicative to extract the LMA components, demonstrating the most significant features for indexing and classification of the performer's feelings; the features succeed to characterise each of the movements, offering new guidelines for the human motion synthesis and comparison methods. Furthermore, we have proved that the performer's acting emotional state and the motion quality based on LMA are highly correlated. A limitation of the proposed methodology is that a subset of the features requires to use 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; we aim to measure the similarity between different feelings and find potential connections, in collaboration with psychologists. In addition, more captures will take place at dance schools to reduce the potential influences of the laboratory environments. We would like to see how much our result will carry to non-dance sequences and to non-acted data. Besides, the results of this paper will be referred to establish a motion classification algorithm; in contrast to the existing techniques, we intend to evaluate movements 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, the feelings and the purpose that has been executed. In addition, motion synthesis approaches will be enriched with the quality characteristics of the action plus the emotion of the performer.

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