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Motion Analysis for Folk Dance Evaluation

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Abstract

*Motion capture techniques are becoming a popular method for digitizing folk dances for preservation and dissemination. Although technically the captured data can be of very high quality, folk dancing, in contrast to choreographed performances, allow for stylistic variations and improvisations that cannot be easily captured by the data themselves. The majority of motion analysis and comparison algorithms are explicitly based on quantitative metrics and thus do not usually provide any insight on style qualities of a performance. In this work, we introduce a motion analysis and comparison framework that is based on Laban Movement Analysis (LMA); these algorithms are particularly useful in the context of teaching folk dances. We present a prototype virtual reality simulator in which users can preview segments of folk dance performed by a 3D avatar and repeat them. The users' performances are captured and subsequently compared to the folk dance template motions. The system then provides intuitive feedback about their performance, which is based on the four LMA components (*BODY, EFFORT, SHAPE, SPACE*) and provides both a quantitative and qualitative evaluation of the performance.*

Categories and Subject Descriptors (according to ACM CCS): I.3.7 [Computer Graphics]: Three-Dimensional Graphics and Realism—Animation

1. Introduction

Cyprus has a rich cultural heritage which, due to its location between three continents, has been influenced by various civilizations. Over the last decade, many works took advantage of the recent technological advances, and have attempted to record, curate, remediate and preserve mostly the tangible part of the Cypriot cultural heritage [SII06, BFG*12]. However, Cypriot cultural heritage also encompasses a range of important intangible assets (e.g., folk dances, songs, handcraft). In this paper, we focus on folk dancing; folk dancing is one of the primary means by which ethnic groups have managed to form and preserve a cultural identity over a period of hundreds of years. Folk dances are learned informally and they are passed on from one generation to the next. The main difference between choreographed dances and folk dances is that the latter are often improvisations by non-professionals that take place in social events and other daily life activities. Folk dancing is a rather "malleable" form of intangible cultural heritage, as it is modified and adapted over time and across different geographic locations. Although each folk dance has a basic set of steps and postures that dominate, folk dancers will typically modify and oftentimes enrich the dance with their personal style. The implication of these stylistic mutations is that there is no single ground truth for a folk dance.

There are mainly two ways to learn dancing. One is to attend a dance lesson, where the teacher demonstrates the moves and guides students to improve their skills in performing the dance. Alternatively, students may choose a self-learning approach, where they observe the moves and practice by themselves, usually through video. Irrespective of the learning method, dance students can quickly learn the choreographic aspects of the dance, e.g. the basic steps and postures, but it may be extremely tedious to master the dynamics of movement (e.g. flow, weight, etc.).

Motion capture technology has enabled the documentation and preservation of intangible cultural heritage artifacts such as folk dances. However, digitization alone is not sufficient to pass folk dancing to the newer generations. Therefore, interactive virtual reality 3D applications, e.g. games [TCL11] and dance learning platforms [MTPK08], have emerged as teaching aids for users wishing to learn how to perform these dances. Dance teaching applications usually feature a virtual 3D teacher who first performs a pre-

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recorded expertly executed dance, or segment of a dance. The user will then perform this motion physically while being monitored by a motion capture system attached to the application. The motion is then analyzed and compared to the teacher's motion and the user is provided with feedback.

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). Stylistic variations, though, are difficult to measure; the movement of the human body is complex and it is hard to completely describe. An important role in the description and categorization of a dance performance is that played by the intensity and fluidity of each movement, reflecting its *nuance*. The *nuance*, along with the shape, the concentration and the energy needed to carry out the action, can provide additional information with regards to the style of the performance. Current dance motion evaluation algorithms fail to acquire the stylistic elements of dance performances (e.g. the emotion, expression, and interaction between the performer and the environment); however, choreographers and movement analysts take into consideration movement characteristics that show the style of the dance which play an important role in the evaluation of movements. Based on the principles of movement observation science, specifically using Laban Movement Analysis (LMA) [Mal87] components, we aim to extract the so-called nuance of motion and use it in motion comparison and evaluation purposes. 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.

In contrast to previous approaches that compare and evaluate dances, our technique uses LMA to qualitatively assess the similarity of two dancing motions. It determines characteristics that a student would find useful for the improvement of his skills. For example, we do not report the angular offset of a student's limbs in comparison to his teacher's. Instead our system generates higher-level hints, such as a percentage of correctness in the flow and intensity of the motion inferred from a large set of low-level motion features. This approach of intuitively exposing the quality aspects of the student's motion makes it easier for him to focus on improving a particular aspect of his performing skills, e.g. his overall posture or his speed, rather than a specific body part.

Apart from contributing a novel motion analysis technique for folk dances, we have also furthered the functionality, as well as enriched the motion capture datasets, provided online via the Dance Motion Capture Database [Uni14]. These mocap datasets are currently the only datasets that are freely available and can be used for reproduction, analysis, documentation, as well as research by other scholars and practitioners of an integral part of Greek and Cypriot intangible cultural heritage.

2. Related Work

Motion matching or comparing algorithms typically use discrete motion samples which represent body postures to compute an aggregate distance metric between the two postures. In literature, the majority of methods can be grouped into those using (i) the distances between the positions of body joints, (ii) the angular differences between respective joint pairs, and (iii) the velocities of respective joints, or a combination of these methods. The wide range of existing techniques for motion analysis, segmentation, classification and retrieval may also be applied to motion captured dances. However, the scientific community has recently focused on explicitly devising methods to cater for dance-oriented applications, such as dance teaching, dancing games, as well as extraction of choreography, dance annotation, comparison, etc. In this work, we are particularly interested in techniques for motion comparison and evaluation.

Motion Graphs [KG04] is a data structure widely used to compare motion clips (i.e. using distance metrics between postures) and generate transitions between them. A content-based retrieval method was introduced by Müller et al. [MRC05] to compute a small set of geometric properties for motion similarity purposes. Different techniques have been proposed for spatial indexing of motion data [KPZ*04, KTWZ10]. Moreover, Deng et al. [DGL09] and Wu et al. [WWX09] cluster motion on hierarchically structured body segments, whereas Chao et al. [CLAL12] use a set of orthonormal spherical harmonic functions.

Most of these techniques can extract similar poses from different motions. However, when evaluating dancing motions for educational purposes the teacher's and the student's motions can be qualitatively similar, although they may technically differ. Thalmann et. al [MTPK08] designed a learning framework for folk dances based on motion capture. They treated the concept of dance holistically without discriminating between movement and context. Within the context of this framework, they developed a web-based 3D environment in which users can visualize folk dances. Alexiadis and Daras [AD14] have recently designed a framework for automatic dance performance evaluation using motion capture data using marker-less motion capture. The authors represented the human motion data as sequences of pure quaternions and subsequently introduced a set of quaternionic vector-signal processing methodologies for dance motion evaluation and comparison purposes. Tang et al. [TCL11] implemented a real-time dancing game using motion capture. The system operates in real time and therefore its response is designed to have low latency. They propose a Progressive Block Matching algorithm to monitor and detect the player's motions and match them against a set of motion templates. Chan et al. [CLTK11] presented a similar system, but focused on performing a comprehensive motion analysis of the player's body parts with respect to the taught motion template. Deng et al. [DLGY11] developed a real-time motion recognition algorithm that is based on a human body partition indexing scheme with flexible matching to determine the end of a move as well as to detect unwanted motion. Yang et al. [YLYD13] furthered this work to provide tools for automatically generating dance lessons that adapt to the skill of the student dancer.

In order to achieve a satisfying simulation for the complex human body language, an as simple as possible, but as complex as necessary description of the human motion is required. LMA [Gue05] satisfies these demands. The EMOTE system, introduced by Chi et al. [CCZB00], synthesises gestures, for motion parameterisation and expression, based on the LMA effort quality; Zhao and Badler [ZB05] used the EMOTE results to design a neural network for gesture animation. Hartmann et al. [HMP06] quantify the expressive content of gesture based on a review of the psychology literature, whereas Torresani et al. [THB06] used LMA for learning motion styles. Lately, Wakayama et al. [WOTO10] and Okajima et al. [OWO12] used a subset of LMA features for motion retrieval, while Kapadia et al. [KCT*13] proposed a method for searching motions in large databases using LMA features. Shiratori et al. [SNI06] used Laban theory for synthesising dance motion matched to music, while Santos and Dias [SD10] presented a tool to describe human basic behaviour patterns using LMA. Masuda et al. [MKI09] also expressed the bodily emotion of a human-form robot using a small set of Laban's features; the authors also added four basic emotions to arbitrary movements [MKI10]. Recently, 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. Aristidou and Chrysanthou [AC13] used a variety of features that encode characteristics of motion using the LMA components to understand the performer emotions from acted dance performances; the same authors, in [AC14], have provided a brief analysis of how these features change on movements with different emotional state, finding movement similarities between different emotional states.

3. Motion Analysis

In this paper we have developed a novel motion comparison algorithm, which compares the movements of two characters by taking into consideration not only the posture matching (meaning the physical geometry of the avatar) but also the style. The proposed evaluation extracts the quality characteristics of a dance performance based on Laban Movement Analysis (LMA); LMA is a language for interpreting, describing, visualizing 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. In this section, we present a subset of the LMA components and the representative features which are indicative to capture the motion properties, and can be used for motion comparison purposes. The proposed LMA features are calculated so as to be used for motion comparison and evaluation purposes; the key joints used for the description of the proposed LMA features are indicated in Figure 1.

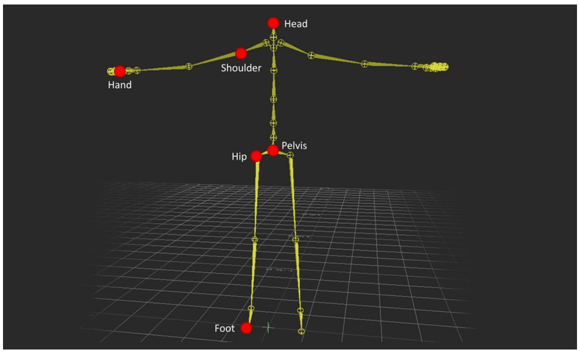


Figure 1: *Representation of the articulated skeletal structure used to calcuate the LMA features. Key joints used in the calculations are clearly indicated.*

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 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 (i) feet - hips (f_1), (ii) hands - shoulders (f_2), (iii) right hand - left hand distance (f_3), (iv) hands - feet distance (f_4), and (v) hands - head distance (f_5) are used to capture the body connectivity and the relation between body parts of the performer.
- Pelvis height (f_6): the distance between the pelvis joint and the ground; this feature is particularly useful for specifying whether the performer kneels, jumps in the air or falls to the ground.
- Gait size (f_7): 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 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_8): 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_9): The Weight factor can be identified by studying how the deceleration of motion varies over time; f_9 is estimated by calculating the deceleration of the pelvis joint. 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: The velocity of the performer's movement is indicative of the Time factor. It is estimated by calculating the distance covered by the pelvis joint over a time period (f_{10}). In addition, the average velocity of both hands (f_{11}) and both feet (f_{12}) 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 ($f_{13} - f_{15}$): 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.
- Jerk (f_{16}): 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 (f_{13}) 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 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 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: The volume of the performer's skeleton is given by calculating the bounding box given from the five end-effector (head, hands and feet) joints (f_{17}). In addition, the volume of all joints (f_{18}) is calculated to separate cases where hands and/or legs are very close to each other, but the performer's volume is still large.
- Torso height (f_{19}): The distance between the head and pelvis 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_{20}): 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.

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_{21}): The distance covered over a time period.
- Area (f_{22}): The total area covered over a time period.

Combining f_{21} and f_{22}, 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. Motion Comparison

The proposed LMA features can be used to extract information with regards to the dance performance, taking into consideration both the body variations, as well as the style of the performance. In that manner, we are able to evaluate a dance performance, and find potential similarities with another, even if the performers' posture geometries have significant differences. In order to assess two performances, and find their potential similarities, we have implemented a motion comparison framework.

Each motion clip has been segmented using a 35-frames moving window with a 10-frames step, so as to draw the proposed LMA features and measure the observations. It is assumed that the clips are already synchronized. 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 70 different feature measurements (ϕ_is). Then, a correlation matrix has been introduced to present the association between the windows of different performances. The correlation matrix measures the Pearson's linear correlation coefficient, that is normalized to take values between 0 and 1 (0 - no correlation, 1 - high correlation). To evaluate the correlation between two performances, each of the four LMA components has been assessed separately, returning a Pearson's linear correlation coefficient for each LMA component; the overall evaluation is a weighted sum of all the LMA components. In this way, we can measure the relevance between two performances for each LMA component separately. Two time-windows are considered similar if their Pearson's linear correlation coefficient is larger than a user-specified threshold, in this work referred to as *decision threshold*, which usually takes values higher than 75%.

Figure 2: *Sample frames from motion captured folk dances contributed to the Dance Motion Capture Database. From left to right, upper row shows Zeimpekiko and 1st Antikristos, while the lower row show 2nd and 3rd Antikristos respectively.*

5. LMA-Based Dance Learning Platform

Dancing is largely taught by example, with a teacher performing the movements and the student repeating. Self-learning of dances has been mainly based on educational video material and more recently video games. In line with other computer-based dance teaching systems in this section we present a prototype self-learning dance platform which is based on our LMA algorithmic framework. The platform takes advantage of high quality 3D motion capture data of folk dances and uses the motion analysis algorithm, presented in Section 3, to provide a set of quality parameters that can be tuned to assess similarity between motions. Furthermore, using the motion comparison algorithm the platform directly leverages the intuitiveness of the LMA framework to provide user-friendly feedback and parameter control. Please note that the dance simulator does not intend to replace traditional dance tuition, but to provide an additional tool for training and education in dance, both at home and at school, using an interactive environment.

5.1. MoCap Folk Dance Data

In parallel to the technical contributions in this work, a considerable effort has been invested in digitizing Cypriot folk dances, as well as acted modern dance performances. The data have been captured using a PhaseSpace's Impulse X2 motion capture system [Pha], which allows for high-frequency optical tracking of the dance performers (up to 960Hz). However, the quality of the data is not only due to the technical equipment used. The performers were experienced dancers of which the majority were active members of cultural organizations and dance schools. Therefore, the motion captured folk dances document an integral part of Cypriot intangible cultural heritage, which were up to now only documented via text, photographs and video. These quality and culturally important datasets have been submitted for the enrichment of the Dance Motion Capture Database [Uni14], which has been initialized by Stavrakis et al. [SAS*12], and can be viewed online using the Unity3D web plug-in in real time. Figure 2 shows snapshots from the folk dances we contributed in the database.

Our datasets comprise of BVH (Biovision Hierarchical Data) files from dance performances; the BVH format 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. It is important to recall that the BVH skeletons in our dataset are normalized, thus skeleton and joint distances, such as arm span and other displacements, are calculated under the same conditions.

5.2. Dance Learning Platform

The prototype learning platform is built around the concept of students observing a virtual 3D teacher performing dance movements and repeating them. It uses quality motion captured folk dance data from the database, as described before. Motion data represent complex dance choreography and thus can be difficult for beginners to perform all at once. Instead, the motion captured data are segmented into dance motion primitives, i.e. short sequences of distinct movements that usually last between 400 and 900 frames. These motion

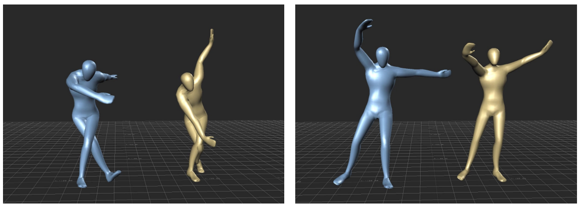


Figure 3: *Snapshots from our experimental data, where the student (in yellow) imitates the teacher's (in blue) movements.*

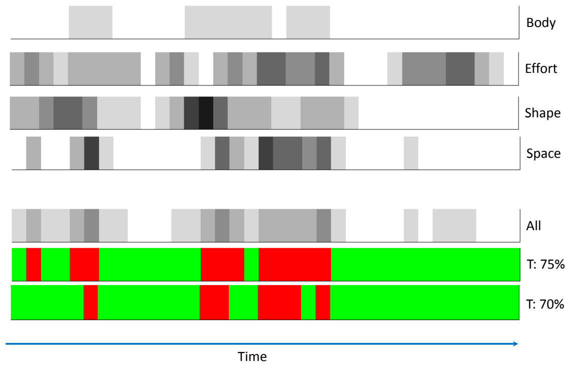


Figure 4: *The correlation between the movements of the teacher and student; the first four bars show the correlation for each LMA component separately, while the next shows the overall correlation taking into consideration all the LMA components. The correlation is presented in grayscale, where white means high correlation and black means no correlation. The last two bars show the decision whether the movements under investigation are similar or not, when the passdecision threshold is set at 75% and 70% respectively. Green means "pass", while red mean "fail".*

primitives act as template motions and can be reassembled into the complete dance.

During a dance learning session the user selects the dance he wants to learn and a 3D avatar (teacher) selects arbitrary dance motion primitives from the template motions and demonstrates it to the user (student). The user then physically performs the motion which is captured and passed to the motion analysis subsystem, via a full body motion capture system. The user's motion is analyzed and compared to the template motion and an evaluation of the user's performance is generated.

In contrast to other dance learning systems, the user is not explicitly provided with feedback on body parts that have been incorrect. We believe that this type of feedback, although quite helpful, can be daunting to beginners. For example, beginners usually find it easier to learn the body posture (BODY) and steps (SPACE) of a dance, but may find it very difficult to reproduce the flow (EFFORT) and shape qualities (SHAPE) of a dance. Instead, the platform generates an evaluation based on the LMA categories (BODY, EFFORT, SHAPE, SPACE), which exactly point the student to the particular quality characteristic of his performance that needs improvement. This way our system can be considered as more forgiving toward mistakes that could demoralize the student and play little educational role for his skill level, such as an incorrectly bend arm or a slightly misplaced foot.

Furthermore, the learning platform allows the user to modify the sensitivity of the system when comparing the motion of the student to the template motions per LMA category. The four LMA categories are initially equally weighted (25% each). Users can manually adjust the weights to tilt the sensitivity toward one of the LMA components of the dance they would like to improve on. For instance, users that are comfortable with their body posture may reduce the decision threshold for the BODY and/or increase the threshold of the EFFORT to make the system more sensitive to mistakes in the fluidity of their motion. In addition, the system can be set to adaptively modify the difficulty of achieving a close match of the template motion. This follows the same principles of dynamic difficulty adjustment (DDA) in computer games, with an outlook of focusing the user's attention to aspects of the motion he needs to improve on.

6. Experimental Results

This section presents the experimental results of the proposed system. Students were asked to imitate short parts of pre-captured dance performances (performed by professional dancers), while their performance was evaluated against the teacher's performance using the proposed LMA based motion comparison approach. Figure 3 shows two snapshots from our video clips; the teacher (in blue) performs a dance choreography, while the student (in yellow) tries to follow it.

Figure 4 shows the correlation between a student and a teacher performance for each LMA component separately (in gray-scale, white means high correlation and black small), as well as the overall correlation when all LMA components are summed. The last two bars show the decision whether these two movements are similar for two cases, when the decision threshold was set at 75% and 70% respectively; when its green, the decision is *positive* (above the threshold), while when its red is *negative* (below the threshold). As expected, the largest deviation is observed in the EFFORT component since the movements of the student are more bound and sudden, while the movement of the trainer are more free and light.

In addition, Figure 5 presents the same example, indicating the correlation between the student and teacher performances with regard to the BODY, EFFORT, SHAPE and SPACE components for each time-window; it also states the overall correlation, while the weight for each component is

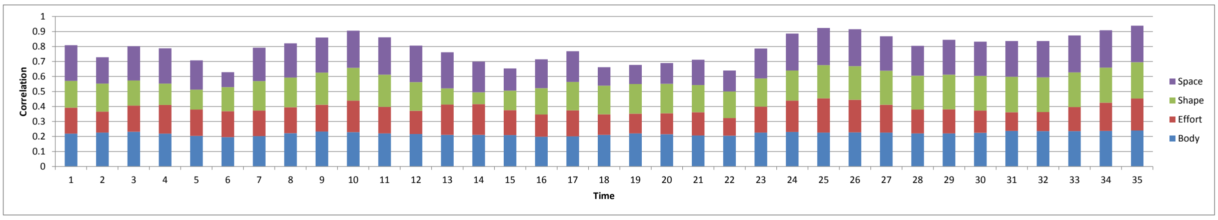


Figure 5: *An example that shows the correlation between the performance of the teacher and the student.*

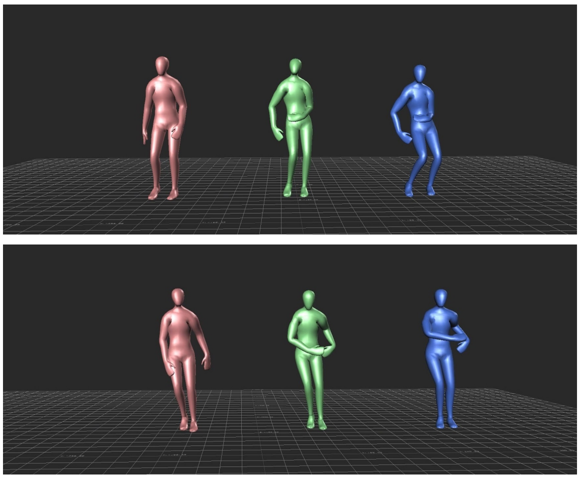


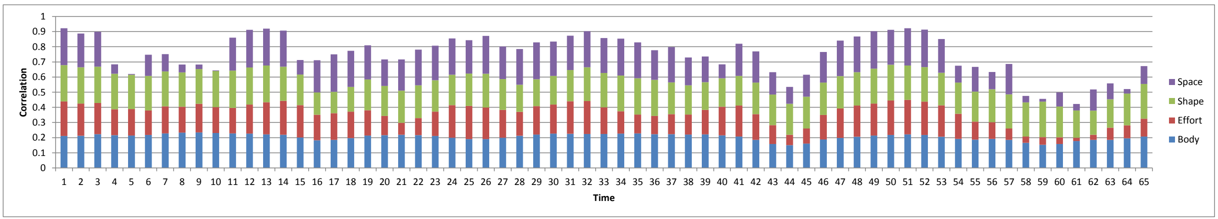
Figure 6: *The dancer performs the same choreography but each time with different intensity; starting from the left to the right, the red avatar presents the choreography with intensity I_1, the green with I_2, and the blue with I_3.*

set to 25%. For instance, in Figure 5, at time-window 10, the BODY correlation is 22.8/25, the EFFORT 21/25, the SHAPE 21.9/25, and SPACE 24.8/25, while the total correlation is summed up to 90.4%. In contrast, at time-window 22 the BODY correlation is 20.5/25, the EFFORT 11.8/25, the SHAPE 17.8/25, and SPACE 13.9/25, ending at a total correlation of 64%.

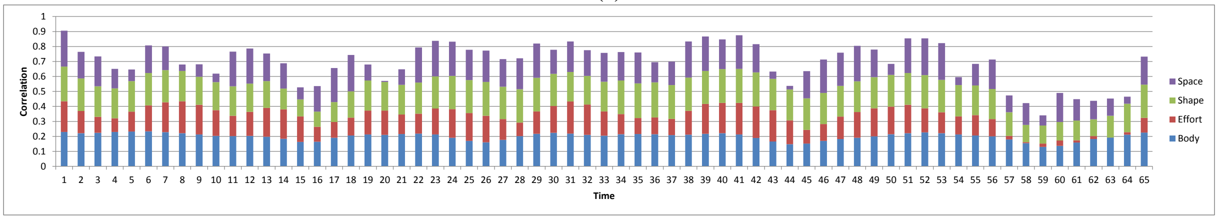
In order to evaluate the ability of our approach to extract the qualitative characteristics of the movement, we asked a professional dancer to perform the same choreography three times, but each time with different intensity (I_1 refers to movement with low intensity, while I_3 to high). Note that, in all cases, the dance steps can be considered as correct, while the intensity may indicate the dance-style. Figure 7 shows the correlation between the performances for each LMA component, as well as the overall correlation. In this example, we have observed that the BODY and SHAPE components appear to have high correlation, especially when the I_2 and I_3 performances were compared, unlike the EFFORT and SPACE, which have smaller correlation. This is more obvious when the performances with intensity I_1 and I_3 were evaluated, which has greater variation in their motion intensity.

The dance learning simulator also offer the possibility to choose different weights for each LMA component, in order the student to focus on individual problems and improve specific skills (based on the LMA components), facilitating the learning of the dance. Figure 8 shows such an example, where the correlation between the performances with intensity I_1 and I_3 have been evaluated, but this time having different weights for each LMA component. For instance, looking at the time-windows 4 and 5, it is easily observed that when all weights are equal (25% for each LMA component), the correlation is 65.1% and 64.7% respectively. However, when the weights were set to 50% for the BODY, and 16.67% for rest component, the correlation was increased to 73.9% and 74.1% respectively, while when the weights were set to 50% for the EFFORT, and 16.67% for the rest, the correlation was reduced to 55.6% and 60.9% respectively. Having in mind that the body movements of the dancer follows the choreography steps correctly, but differs in the intensity of the movements, we can safely conclude that our method can effectively extract the qualitative and stylistic features of the motion.

The proposed evaluation model allows further customization of the assessment criteria in accordance with the anatomical characteristics of the trainee. Apparently the trainee is not as fit as the trainer, who is a professional dancer, nor has the same flexibility. For instance, the student may not have the same stretching as the teacher, resulting in smaller openings (e.g. of the legs). Using the proposed method, the weight of specific features can be selectively reduced (while others increased), so as to have less impact on the overall evaluation of motion. In addition, by observing the maximum and minimum values for specific features of the student's and the teacher's performance (especially features of the BODY component), we can use a proportional approach that considers the stretching capabilities of the performer. Finally, it is important to note that the head orientation (f_8), which offers indications about the immediacy of motion, is not contributing in the evaluation process in cases where the student is amateur. In such case, where the trainee does not know the steps of the dance and his head is con-



(a)



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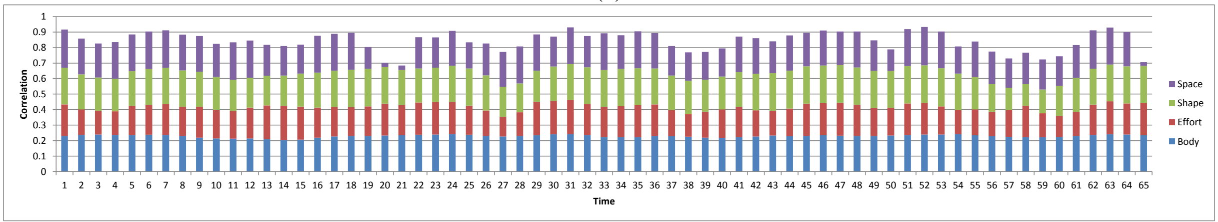


(c)

Figure 7: *The correlation between three performances with different intensity (I) when the weight factor for each LMA component is set to 25% - I_1 indicates low intensity, while I_3 large. (a) I_1 compared to I_2, (b) I_1 compared to I_3, and (c) I_2 compared to I_3.*

stantly turned towards the screen, no additional information is offered with regards to the style and quality of the movement, apart that the head is disoriented.

Our method is able to evaluate the performance of a dance and find its correlation with another, comparing both the bodily and stylistic characteristics of motion. We have segregated the evaluation into four main categories, that are based on the LMA theories, so as to help both the trainer, as well as the trainee, to identify potential errors on his performance and improve specific skills. The results confirm the effectiveness of our method, opening new horizons for automatic motion and dance evaluation processes.

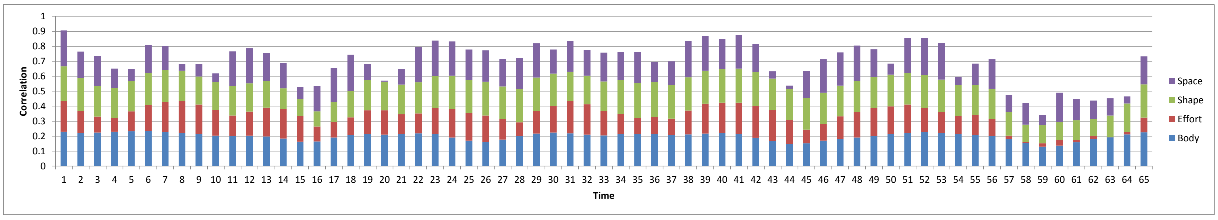
A limitation of the proposed methodology is that a subset of the features requires the use of a short time-window, resulting in delays in the extraction of the performance characteristics. In addition, since the mocap systems are expensive, the performances of the student may be captured using a Kinect multi-synchronized architecture, such as the one proposed by [KDY*14].

7. Conclusions and Future Work

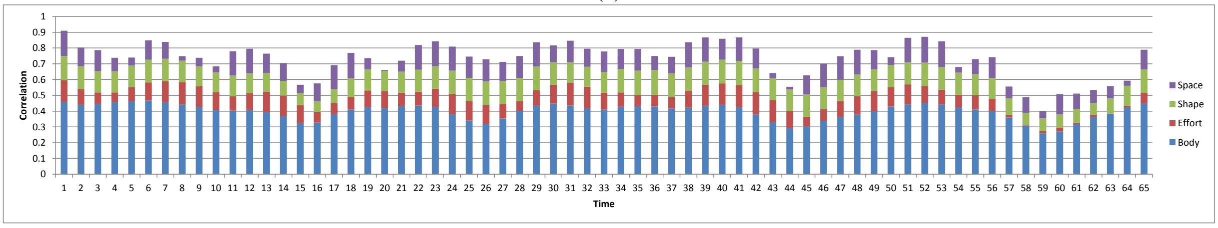
In this paper we have developed a novel motion comparison algorithm, which compares the movements of two avatars taking into consideration not only the posture matching (meaning the physical geometry of the avatar) but also the style, including the required effort, shape, and interaction of the performer with the environment. Theories which have been applied in movement analysis and education over the last century have been studied and incorporated to establish algorithms for motion comparison and evaluation. Preliminary results demonstrate the effectiveness of our method to extract qualitative and quantitative characteristics of the movement, while dance performances can be evaluated based on the LMA components. Our method also offers the possibility to compare two performances having different weights of influence for each LMA component, giving the opportunity to the instructor, or the user, to adjust the dance teaching simulator on his needs.

We aim to extend the proposed dance teaching simulator, so as to work alongside with the Dance Motion Capture database; in that manner, it will constantly be enriched with new clips and data as soon as they are available. Future work will see the introduction of a large variety of different dances and performances, so as to establish a more complete motion capture dance library.

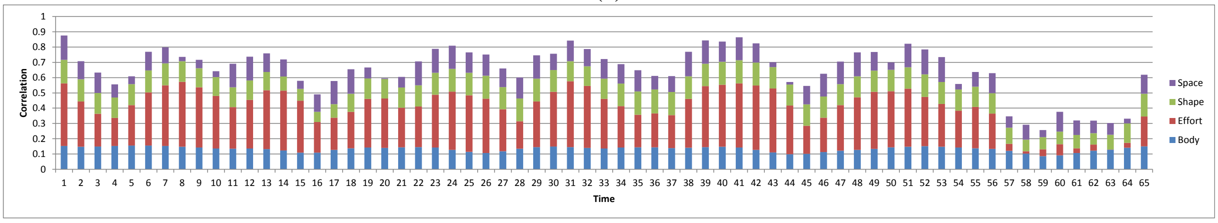
In addition, for a real-time dance evaluations system, it is



(a)



(b)



(c)

Figure 8: *The correlation when two similar performances with different intensity are compared. (a) I_1 compared to I_3 with weights:* BODY, EFFORT, SHAPE *and* SPACE *at 25%, b) I_1 compared to I_3 with weights:* BODY *at 50%, while* EFFORT, SHAPE *and* SPACE *at 16.67%, and (c) I_1 compared to I_3 with weights:* EFFORT *at 50%, while* BODY, SHAPE *and* SPACE *at 16.67%.*

a requirement to develop better motion synchronization and segmentation techniques, so as to take into consideration the experience of the user; for instance, different synchronization and evaluation approaches should be considered for amateur or expert dancers since the first user needs more time to see and perform, while the latter can do it almost immediately.

The next step is to design enhanced learning tools and processes for teaching and learning dance through understanding and observing one's own movement. The outcome will be a virtual teacher that demonstrates dance through a whole-body interaction environment, giving feedback of the performance to both the trainer and the trainee. This learning simulator will aim to help students develop critical skills on movement and enhance their movement literacy (ability to understand and describe their motion).

Finally, while we have focused on introducing qualitative dance comparison methods using LMA, the dance teaching system will have to be formally evaluated with human participants to establish its effectiveness.

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References

[AC13] ARISTIDOU A., CHRYSANTHOU Y.: Motion indexing of different emotional states using LMA components. In *SIGGRAPH Asia 2013 Technical Briefs* (New York, NY, USA, 2013), SA '13, ACM, pp. 21:1–21:4. 3

[AC14] ARISTIDOU A., CHRYSANTHOU Y.: Feature extraction for human motion indexing of acted dance performances. In *Proceedings of the 9th International Conference on Computer Graphics Theory and Applications* (2014), GRAPP '14, pp. 277–287. 3

[AD14] ALEXIADIS D. S., DARAS P.: Quaternionic signal processing techniques for automatic evaluation of dance performances from mocap data. *IEEE Transactions on Multimedia*, 99 (April 2014), 1–16. 2

[BFG*12] BARIAMI G., FAKA A., GEORGOPOULOS A., IOANNIDES M., SKARLATOS D.: Documenting an UNESCO WH site in cyprus with complementary techniques. In *Proceedings of the 4th International Conference on Progress in Cultural*

Heritage Preservation (EuroMed '12) (Limassol, Cyprus, 2012), vol. 7616, LNCS, pp. 27–32. 1

[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. 3

[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. 2

[CLTK11] CHAN J., LEUNG H., TANG J., KOMURA T.: A virtual reality dance training system using motion capture technology. *IEEE Transactions on Learning Technologies 4*, 2 (April 2011), 187–195. 2

[DGL09] DENG Z., GU Q., LI Q.: Perceptually consistent example-based human motion retrieval. In *Proceedings of I3D '09* (NY, USA, 2009), ACM, pp. 191–198. 2

[DLGY11] DENG L., LEUNG H., GU N., YANG Y.: Real-time mocap dance recognition for an interactive dancing game. *Computer Animation and Virtual Worlds 22*, 2-3 (2011), 229–237. 3

[Gue05] GUEST A. H.: *Labanotation: The System of Analysing and Recording Movement*, 4th ed. Routledge, 2005. 3

[HMP06] HARTMANN B., MANCINI M., PELACHAUD C.: Implementing expressive gesture synthesis for embodied conversational agents. In *Proceedings of GW'05* (2006), Springer-Verlag, pp. 188–199. 3

[KCT*13] KAPADIA M., CHIANG I.-K., THOMAS T., BADLER N. I., KIDER JR. J. T.: Efficient motion retrieval in large motion databases. In *Proceedings of I3D '13* (NY, USA, 2013), ACM, pp. 19–28. 3

[KDY*14] KITSIKIDIS A., DIMITROPOULOS K., YILMAZ E., DOUKA S., GRAMMALIDIS N.: Multi-sensor technology and fuzzy logic for dancer motion analysis and performance evaluation within a 3d virtual environment. In *Design and Development Methods for Universal Access in Human-Computer Interaction.*, vol. 8513 of *LNCS*. Springer International Publishing, 2014, pp. 379–390. 8

[KG04] KOVAR L., GLEICHER M.: Automated extraction and parameterization of motions in large data sets. *Transactions on Graphics 23*, 3 (2004), 559–568. 2

[KPZ*04] KEOGH E., PALPANAS T., ZORDAN V. B., GUNOPULOS D., CARDLE M.: Indexing large human-motion databases. In *Proceedings of VLDB* (2004), pp. 780–791. 2

[KTWZ10] KRÜGER B., TAUTGES J., WEBER A., ZINKE A.: Fast local and global similarity searches in large motion capture databases. In *Proceedings of SCA '10* (2010), pp. 1–10. 2

[Mal87] MALETIĆ V.: *Body, Space, Expression: The development of Rudolf Laban's Movement and Dance Concepts*. Approaches to semiotics. De Gruyter Mouton, 1987. 2

[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 Berlin Heidelberg, 2009, pp. 322–334. 3

[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 Berlin Heidelberg, 2010, pp. 49–60. 3

[MRC05] MÜLLER M., RÖDER T., CLAUSEN M.: Efficient content-based retrieval of motion capture data. *Transactions on Graphics 24*, 3 (2005), 677–685. 2

[MTPK08] MAGNENAT-THALMANN N., PROTOPSALTOU D., KAVAKLI E.: Learning how to dance using a web 3d platform. In *Advances in Web Based Learning - ICWL 2007*, vol. 4823 of *LNCS*. Springer Berlin Heidelberg, 2008, pp. 1–12. 1, 2

[OWO12] OKAJIMA S., WAKAYAMA Y., OKADA Y.: Human motion retrieval system based on LMA features using IEC method. In *Innovations in Intelligent Machines* (2012), pp. 117–130. 3

[Pha] PhaseSpace Inc: Optical Motion Capture Systems. http://www.phasespace.com. 5

[SAS*12] STAVRAKIS E., ARISTIDOU A., SAVVA M., LOIZIDOU HIMONA S., CHRYSANTHOU Y.: Digitization of cypriot folk dances. In *Proccedings of the 4th International Conference on Progress in Cultural Heritage Preservation, (EuroMed '12)* (Limassol, Cyprus, 2012), vol. 7616, LNCS, pp. 404–413. 5

[SD10] SANTOS L., DIAS J.: Laban movement analysis towards behavior patterns. In *Emerging Trends in Technological Innovation*, vol. 314 of *Advances in Information and Communication Technology*. Springer Berlin Heidelberg, 2010, pp. 187–194. 3

[SI06] SOFOCLEOUS E., IOANNIDES M., IOANNIDES C.: The geometric documentation of the asinou church in cyprus. In *Proceedings of the 7th International Symposium on Virtual Reality, Archaeology and Cultural Heritage* (2006), VAST '06, Eurographics Symposium Proceedings, pp. 138–144. 1

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

[TCL11] TANG J. K. T., CHAN J. C. P., LEUNG H.: Interactive dancing game with real-time recognition of continuous dance moves from 3d human motion capture. In *Proceedings of the 5th International Conference on Ubiquitous Information Management and Communication* (New York, NY, USA, 2011), ICUIMC '11, ACM, pp. 50:1–50:9. 1, 2

[THB06] TORRESANI L., HACKNEY P., BREGLER C.: Learning motion style synthesis from perceptual observations. In *Proceedings of NIPS'06* (December 4-7 2006), pp. 1393–1400. 3

[Uni14] UNIVERSITY OF CYPRUS: Dance Motion Capture Database: http://dancedb.cs.ucy.ac.cy/, accessed 25/05/2014. 2, 5

[WOTO10] WAKAYAMA Y., OKAJIMA S., TAKANO S., OKADA Y.: IEC-based motion retrieval system using laban movement analysis. In *Proceedings of KES'10* (2010), pp. 251–260. 3

[WWX09] WU S., WANG Z., XIA S.: Indexing and retrieval of human motion data by a hierarchical tree. In *Proceedings of VRST* (NY, USA, 2009), ACM, pp. 207–214. 2

[YLYD13] YANG Y., LEUNG H., YUE L., DENG L.: Generating a two-phase lesson for guiding beginners to learn basic dance movements. *Computers & Education 61* (2013), 1–20. 3

[ZB05] ZHAO L., BADLER N. I.: Acquiring and validating motion qualities from live limb gestures. *Graphical Models 67*, 1 (2005), 1–16. 3

[ZGCA13] ZACHARATOS H., GATZOULIS C., CHRYSANTHOU Y., ARISTIDOU A.: Emotion recognition for exergames using Laban Movement Analysis. In *Proceedings of Motion in Games* (New York, NY, USA, 2013), MIG '13, ACM, pp. 39–44. 3