LMA-Based Motion Retrieval for Folk Dance Cultural Heritage

Andreas Aristidou, Efstathios Stavrakis, and Yiorgos Chrysanthou

University of Cyprus, P.O. Box 20537, 1678 Nicosia, Cyprus
a.aristidou@ieee.org,{stathis,yiorgos}@cs.ucy.ac.cy

Abstract. Motion capture (mocap) technology is an efficient method for digitizing art-performances, and it is becoming a popular method for the preservation and dissemination of dances. However, stylistic variations of human motion are difficult to measure and cannot be directly extracted from the motion capture data itself. In this work, we present a framework based on Laban Movement Analysis (LMA) that aims to identify style qualities in motion and provides a mechanism for motion indexing using the four LMA components (Body, Effort, Shape, Space), which can also be subsequently used for intuitive motion retrieval. We have designed and implemented a prototype motion search engine in which users can perform queries using motion clips in a folk dance database. Results demonstrate that the proposed method can be used in place, or in combination with text-based queries, to enable more effective and flexible motion database search and retrieval.

Keywords: Folk dance library, Laban Movement Analysis, motion analysis, motion capture, motion searching.

1 Introduction

Folk dancing is performed, usually spontaneously, at social events and gatherings by non-professionals. It is not based on a strict choreography and is learned through observation and informal coaching, usually by the elders. Folk dancers learn the basic steps and moves of a folk dance, but may choose to modify or enrich it with improvisations. Folk dances may be performed differently according to their locality, or the cultural background and skill of the individual performers. A representative example is the Zeibekiko folk dance, which is popular among Greek ethnic groups and often includes various feats, such as standing on chairs or lifting objects, etc.

In recent years the attention of a number of scientists and media artists has been drawn to utilizing existing, and developing new, technologies for the preservation and dissemination of folk dance Intangible Cultural Heritage (ICH). Folk dancing presented the CH community with a challenging example of ICH assets that not only require special methods and equipment for recording and archiving them, but are also inherently difficult to index, compare and retrieve. Solving these problems will enable our generation to bequeath a rich, well-organized and spherically analyzed set of folk dance data to the next generation.

M. Ioannides et al. (Eds.): EuroMed 2014, LNCS 8740, pp. 207–216, 2014.

Motion capture (mocap) technologies have shown promise for the preservation of dance performances, alongside video recording, while on the other hand, Virtual Environments have become indispensable from dance training software systems that are popular among end users (i.e. in the form of 3D games). There are several advantages motion capture has over other methods (e.g. video), the most important one being the ability to reconstruct and view moments in a dance from arbitrary viewpoints, which is a significant improvement over fixed-resolution and single-viewpoint videos. Motion captured dance data also facilitate further automated analysis of the movements that may enable the ICH scientific community to delve into more intricate research questions. Automatic motion evaluators or motion search engines that are not based on simple keyword queries can be particularly useful for cross-cultural research and next generation online applications.

Folk dances cannot be characterized by the figure and pose of a performer alone. Motion is characterized by two main aspects; body geometry that describes basic human actions (e.g. walking, running, or jumping) and style, which is given by the emotion, intention, expression, or gender of the performer. The stylistic variations of the movement, which reflect the motion *nuance*, are complex, thus difficult to measure. Based on the principles of movement observation science, specifically using Laban Movement Analysis (LMA) [1] components, we aim to extract the so-called nuance of motion and use it for motion indexing and comparison. LMA is a multidisciplinary system, which incorporates contributions from anatomy, kinesiology and psychology that draws on Rudolph Laban's theories to describe, interpret and document human movements.

We have recently designed a novel motion similarity function based on LMA components [2], which compares motions by taking into consideration not only the physical geometry of the human body, but also the stylistic characteristics of the dancing movements, such as the required energy and fluidity, as well as the emotion, intention and interaction of the performer with the environment. Based on this motion similarity function and a set of high-level values for the stylistic parameters, in this work we present a method for comparing and retrieving motions from a motion database, using an example motion as the search query.

2 Related Work

Capturing and organizing motion data in a systematic manner enables a multitude of applications to be developed, such as motion search engines and dance training systems. Thalmann et. al [3] designed a learning framework for folk dances based on motion capture. They treated the concept of dance holistically without discriminating between movement and context. Based on this framework, they developed a web-based 3D environment in which users can view and learn folk dances. Golshani et al. [4] presented a multimedia information system that can be used to store a variety of dance-related data (e.g. photographs, audio, video, motion data, etc.), and proposed strategies for feature extraction and analysis of this data, useful for cross cultural dance studies. More recently, Kim [5] presented ChoreoSave, a prototype of an online digital dance preservation solution that identifies components comprising a dance work and how such components can be represented using existing software. Stavrakis et al. [6] presented a prototype virtual folk dance teacher and a small digital archive of folk dances (Dance Motion Capture Database [7]), aiming to preserve the cultural heritage of the Cypriot dance tradition.

Motion data have been successfully used to visualize, edit and compose choreography in conjunction with dance notation [8]. Algorithms for motion comparison [9,10] are also actively pursued since they enable searching, synthesizing and evaluating motion sequences. Motion Graphs [11] is a data structure widely used to compare motion clips (i.e. using distance metrics between postures) and generate transitions between them. A variety of different approaches have been proposed for spatial indexing of motion data [12]. Keogh et al. [13] present a method that allows a uniform scaling across the query motion to find matches in motion clips; rather than searching through all scaling of a given motion, they introduced a method for calculating a lower bound on the distance between two motions. Deng et al. [14] and Wu et al. [15] cluster motion on hierarchically structured body segments, whereas Chao et al. [16] use a set of orthonormal spherical harmonic functions. Forbes and Fiume [17] use Principal Component Analysis (PCA) to reduce the dimensionality of motion clips; using weights, they project joints into the PCA space. They then use an Euclidean distance metric to compare a query motion to the motion clips in the PCA space. In a similar way, Liu et al. [18] normalized all poses so as to have the same root and orientation; then, the authors applied a piecewise-linear modeling method which determines a set of principal markers from motion capture systems and constructs a hierarchical model which is used for searching motion queries.

Müller et al. [19], instead of using numerical values such as joint positions and angles, they characterized motion using relational and geometric features; Later, Müller and Röder [20] extended their work by introducing motion templates (MT) to find logically related motions for automatic classification and retrieval of motion capture data. Similarly, Kapadia et al. [21] encoded structural, geometric and dynamic features of motion as keys, as part of an indexing process and for searching complex motions in large motion databases. These keys can then be combined to specify search queries to retrieve motions. El Raheb and Ioannides [22] developed a Dance Ontology (DanceOWL) that describes dance moves based on the Labanotation system, and supports semantic search.

3 Motion Analysis

Laban Movement Analysis is a language for interpreting, describing, visualizing and notating all kinds 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 introduce the LMA components and their representative features (fs) which are indicative to capture the motion properties; a more detailed description of the proposed LMA features is available in [2], which is complementary to this paper and demonstrates a motion evaluation approach for a dance teaching simulator. The proposed framework extracts the LMA components that are used for searching potential similarities between different clips; the LMA features, in contrast to numeric methods used widely in motion analysis literature, offer a qualitative and intuitive description of the movement.

Body Component: The Body component primarily develops body connections. It describes the structural and physical characteristics of the human body and it is responsible for identifying which body parts are moving, which parts are connected, which parts are influenced by others, what the sequence of the movement between the body parts is, and general properties of body organization. The Body component can be calculated using a variety of feature measurements such as different body-parts displacements, gesture orientations, joint distances which give indication whether the performer jumps or kneels, and gait size.

Effort Component: The Effort component describes the intention and the dynamic quality of the movement, the texture, the feeling tone and how energy is being used in 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 being 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 to emotional changes and are essential for capturing the performance's expressiveness. The Effort factors can be derived using features such as different joint velocities and accelerations (time factor), head orientation (space factor) that gives indication whether a movement is direct or indirect, motion deceleration (weight factor), and jerk (flow factor).

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 by calculating the volume of the performer, the torso height, which indicates whether the performer is crouching, and the relation of the hands' position with regards to the body.

Space Component: Space describes the movement in relation to the environment, pathways, and lines of spatial tension. Laban classified the principles for movement orientation based on the body kinesphere (the space within reach of the body, the 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). The Space factor can be derived by measuring the distance and the area covered by the performer over a time period.

4 Motion Searching Engine

In this section we describe a motion search algorithm based on the LMA components computed using the motion analysis technique described in Section 3. To facilitate the search algorithm we have motion captured a set of Cypriot folk dances which we have submitted to the online Dance Motion Capture Database [7]. To ensure the performances are sufficiently well documented, recorded and archived, they were captured directly from experienced dancers using the PhaseSpace Impulse X2 optical motion capture system that is able to record motion with high accuracy and fast capture rate (up to $960Hz$).

Figure 1 shows snapshots from one of the folk dance performances (Cypriot folk: 1^{st} Antikristos) we have contributed in the database. Using the proposed LMA features, we extract the postural and stylistic characteristics of the dance performances, which can then be used to compare motions to find similarities. Thus, the database search functionality can now be improved to include searches that go beyond the use of text keywords and tags. We have designed and implemented a prototype 3D application in which the user can search the database by providing a motion clip as the query and a set of weights for the 4 LMA components. Using this query-by-example paradigm the search capabilities extend to retrieving variations of a folk dance that may exist in the database. For example, our motion search engine was able to retrieve two different performances of a Greek Zeibekiko dance, one fast and one slow, despite being geometrically very different.

In a pre-processing step, each motion has been segmented using a 35-frames moving window within which the LMA components (Body, Effort, Shape, Space) were computed from lower level features, as outlined in Section 3 and described in detail in [2]. These lower level metrics include each feature's maximum, minimum, the mean and the standard deviation, resulting in 70 different measurements (ϕs) that characterize a motion within a window. Then, a correlation matrix has been introduced to present the association between the windows of two performances; each window from the example motion is

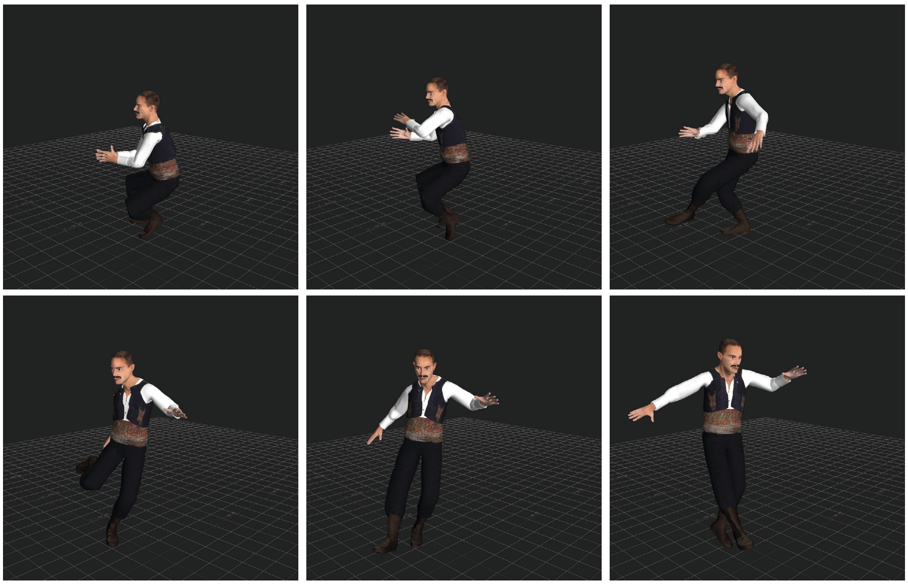

Fig. 1. Snapshots from motion capture data we have contributed in the Dance Motion Capture Database; in this example, the performer is dancing 1^{st} Antikristos, a Cypriot folk dance

compared against all windows of another motion. A correlation matrix is computed for each pair of example motion segment and database motion. 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 motions for each LMA component separately. Two time-windows are considered similar if their Pearson's linear correlation weighted sum is larger than a user-specified threshold, we refer to as the *decision threshold*, which usually takes values higher than 85%.

Users of the query-by-example search algorithm select a contiguous set of frames from any motion clip in the database and supply the weights for the 4 LMA components as percentages. They also provide a value for the decision threshold to enable filtering the amount of results the search engine returns. The engine returns those motion segments of each motion in the database the decision threshold is above the user-supplied valued. The results are ordered from the most highly correlated segments to the least. This query-by-example procedure is briefly summarized in Figure 2.

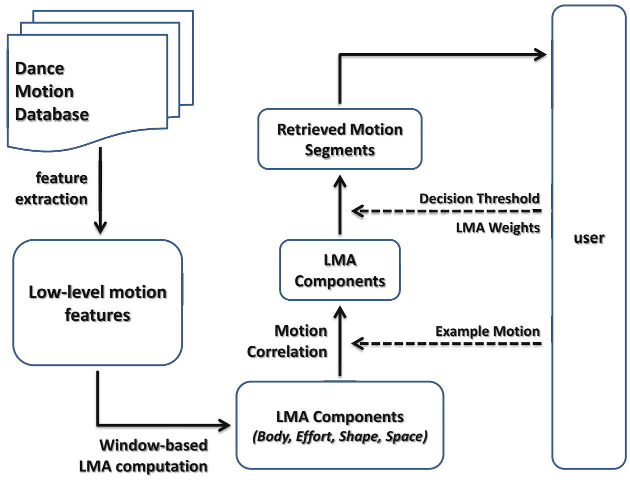

Fig. 2. Flow diagram of the motion analysis and user query-by-example

5 Experimental Results

This section presents the experimental results of the proposed searching engine scheme. We have used five example motion sequences to perform database queries. Our prototype contains 10 folk dances that are approximately 3 minutes long, each, at 30 frames per second.

Figure 3 shows an example where a motion segment (first row) used as the database motion query. It is important to note that due to the mathematical formulation of computing the LMA components our method is invariant to the performer's orientation and position in the world coordinates and can be viewed from any point of view. The 3 best matching motion segments retrieved from the ten folk dances are shown in the 3 rows below the query motion and have with a correlation of 92.8%, 88% and 93.8% respectively (whereas the decision threshold is 85%). The LMA components are all equally weighted (at 25% each) for this example.

Our method facilitates searching motion data stored in databases using intuitive parameters, such as the LMA components. It enables to weight LMA components arbitrarily in order to provide emphasis on those quality characteristics of the motion they are most interested in, without the need to specify individual geometric parameters or limbs. Our approach trades off the ability to formulate granular and more elaborate motion queries offered by other methods (e.g. [21]) for user-friendliness and intuitiveness. In addition, it focuses primarily on retrieving motion with similar qualities and style, rather than similar geometric properties and posture.

Our prototype motion database search application is shown in Figure 4. In the foreground of the figure the motion clip used as a search query within the

Fig. 3. The first row shows frames from the motion query segment (start frame 1590). The second, third and fourth rows show the most similar motion segments.

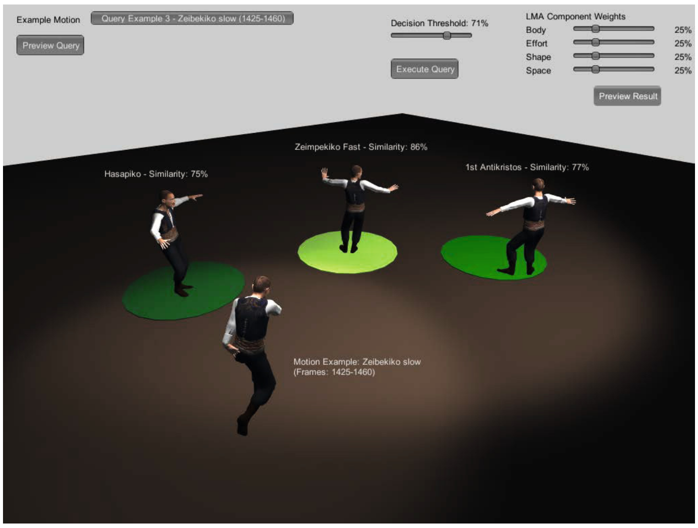

Fig. 4. Snapshots of our motion search prototype 3D application. In the foreground the example motion used as the database query is shown, while in the background previews of dance segments with Pearson correlation coefficient higher than the decision threshold are presented. The user can interactively set a small set of parameters, such as the LMA weights and the decision threshold.

database is shown. In the background the best three matches to the motion query are presented. These results are motion segments attached to virtual characters and represent the frames from the original folk dances that have a higher correlation to the example than the decision threshold. The user has the ability to select the weight of each LMA component (in this example weights are equally set at 25%) and the decision threshold (in this case 71%). The disc, each 3D character is positioned on, is colored with a green color, from bright to dark, to indicate visually the correlation values (brighter means higher correlation). The fast variation of Zeimpekiko has the highest correlation of 86% to the example motion, while 1^{st} Antikristos has a lower correlation of 77% and Hasapiko has the lowest correlation of 75%. Note that the retrieved results are motion segments and the user can also preview temporally these results, along with the example motion.

6 Conclusions and Future Work

In this paper, we have introduced a new approach for content-based retrieval of dance motion capture data based on LMA components; the proposed LMA features describe both the bodily and stylistic characteristics of a dance, while they are able to reveal the main aspects of human creativity such as the style, intentions, expression and derived feeling of a human performance. We have integrated our algorithms into a prototype 3D application that can be used to perform motion queries in a folk dance motion capture database.

In future work, we will digitize more solo and/or group dance performances to enrich the existing dance motion capture database. Our aim is to construct and annotate the motion data pursuant to EUROPEANA formats and regulations. The proposed dance database could also be utilized for dance similarity comparisons and dance training applications. Using the aforementioned motion similarity algorithm cross-cultural comparison may be performed by experts between folk dances from neighboring countries (dance ethnography). Finally, the proposed similarity function will be incorporated into a motion synthesis framework to enable synthesizing novel folk dance motion sequences. Other future work could focus on digitizing facial expressions and hand movements, which our current data do not include.

Acknowledgments. This work is co-financed by the European Regional Development Fund and the Republic of Cyprus through the Research Promotion Foundation under contract DIDAKTOR/0311/73

References

1. Maletić, V.: Body, Space, Expression: The development of Rudolf Laban's movement and dance concepts. In: Approaches to Semiotics. De Gruyter Mouton (1987)
2. Aristidou, A., Stavrakis, E., Chrysanthou, Y.: Motion analysis for folk dance evaluation. In: EG Workshop on Graphics and Cultural Heritage, GCH 2014. Eurographics (2014)

3. Magnenat-Thalmann, N., Protopsaltou, D., Kavakli, E.: Learning how to dance using a web 3D platform. In: Leung, H., Li, F., Lau, R., Li, Q. (eds.) ICWL 2007. LNCS, vol. 4823, pp. 1–12. Springer, Heidelberg (2008)
4. Golshani, F., Vissicaro, P., Park, Y.: A multimedia information repository for cross cultural dance studies. Multimedia Tools and Applications 24(2), 89–103 (2004)
5. Kim, E.S.: Choreosave: A digital dance preservation system prototype. Proc. of the American Society for Info. Science & Technology 48(1), 1–10 (2011)
6. Stavrakis, E., Aristidou, A., Savva, M., Himona, S.L., Chrysanthou, Y.: Digitization of cypriot folk dances. In: Ioannides, M., Fritsch, D., Leissner, J., Davies, R., Remondino, F., Caffo, R. (eds.) EuroMed 2012. LNCS, vol. 7616, pp. 404–413. Springer, Heidelberg (2012)
7. University of Cyprus. Dance Motion Capture Database: `http://dancedb.cs.ucy.ac.cy/` (accessed May 25, 2014)
8. Calvert, T., Wilke, L., Ryman, R., Fox, I.: Applications of computers to dance. IEEE Comp. Graphics Applications 25(2), 6–12 (2005)
9. Raptis, M., Kirovski, D., Hoppe, H.: Real-time classification of dance gestures from skeleton animation. In: Proc. of SCA 2011, pp. 147–156. ACM (2011)
10. Chan, J.C.P., Leung, H., Tang, J.K.T., Komura, T.: A virtual reality dance training system using motion capture technology. IEEE Trans. on Learning Technologies 4(2), 187–195 (2011)
11. Kovar, L., Gleicher, M., Pighin, F.: Motion graphs. Trans. on Graphics 21(3), 473–482 (2002)
12. Krüger, B., Tautges, J., Weber, A., Zinke, A.: Fast local and global similarity searches in large motion capture databases. In: Proc. of SCA 2010, pp. 1–10. Eurographics (2010)
13. Keogh, E., Palpanas, T., Zordan, V.B., Gunopulos, D., Cardle, M.: Indexing large human-motion databases. In: Proc. of VLDB, pp. 780–791 (2004)
14. Deng, Z., Gu, Q., Li, Q.: Perceptually consistent example-based human motion retrieval. In: Proc. of I3D 2009, pp. 191–198. ACM (2009)
15. Wu, S., Wang, Z., Xia, S.: Indexing and retrieval of human motion data by a hierarchical tree. In: Proc. of VRST, pp. 207–214. ACM (2009)
16. Chao, M.-W., Lin, C.-H., Assa, J., Lee, T.-Y.: Human motion retrieval from hand-drawn sketch. IEEE Trans. on Visualization and Computer Graphics 18(5), 729–740 (2012)
17. Forbes, K., Fiume, E.: An Efficient Search Algorithm for Motion Data Using Weighted PCA. In: Proc. of SCA 2005, pp. 67–76. ACM (2005)
18. Liu, G., Zhang, J., Wang, W., McMillan, L.: A system for analyzing and indexing human-motion databases. In: SIGMOD 2005, pp. 924–926 (2005)
19. Müller, M., Röder, T., Clausen, M.: Efficient content-based retrieval of motion capture data. Trans. on Graphics 24(3), 677–685 (2005)
20. Müller, M., Röder, T.: Motion templates for automatic classification and retrieval of motion capture data. In: Proc. of SCA 2006, pp. 137–146. Eurographics (2006)
21. Kapadia, M., Chiang, I., Thomas, T., Badler, N.I., Kider, J.T.: Efficient motion retrieval in large motion databases. In: Proc. of I3D 2013, pp. 19–28. ACM (2013)
22. El Raheb, K., Ioannidis, Y.: Dance in the world of data and objects. In: Nesi, P., Santucci, R. (eds.) ECLAP 2013. LNCS, vol. 7990, pp. 192–204. Springer, Heidelberg (2013)