MULTI-MODAL ANALYSIS OF DANCE PERFORMANCES FOR MUSIC-DRIVEN CHOREOGRAPHY SYNTHESIS

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ABSTRACT

We propose a framework for modeling, analysis, annotation and synthesis of multi-modal dance performances. We analyze correlations between music features and dance figure labels on training dance videos in order to construct a mapping from music measures (segments) to dance figures towards generating music-driven dance choreographies. We assume that dance figure segment boundaries coincide with music measures (audio boundaries). For each training video, figure segments are manually labeled by an expert to indicate the type of dance motion. Chroma features of each measure are used for music analysis. We model temporal statistics of such chroma features corresponding to each dance figure label to identify different rhythmic patterns for that dance motion. The correlations between dance figures and music measures, as well as, correlations between consecutive dance figures are used to construct a mapping for music-driven dance choreography synthesis. Experimental results demonstrate the success of proposed music-driven choreography synthesis framework.

Index Terms**—** multimodal dance modeling, music-driven dance choreography synthesis

1. INTRODUCTION

Dance is a collective union of the music and the human body movements. Automatic dance analysis, annotation and synthesis have been studied extensively in the literature with emphasis on human body motion analysis/synthesis and dance music analysis whereas there is relatively little work on the open problem of music-driven automatic dance synthesis as we address in this paper.

One of the early dance notation systems for human body motion, known as Labanotation, defines a data format to record human dance figures with graphical symbols that provides a detailed sequence of changes in human posture during a dance figure [1]. In [2], Li et al. segment body motions into textons, each of which was modeled by a linear dynamic system, to synthesize human body motion in a manner statistically similar to the original motion capture data by considering the likelihood of switching from one texton to the next. In [3], Ruiz and Vachon perform analysis of dance figures in a chain of simple steps using HMMs to perform automatic recognition of basic movements in the contemporary dance.

Dance music analysis in general includes beat and tempo tracking, measure analysis, and rhythm and melody detection. In [4], Gao and Lee propose an adaptive learning approach to analyze music tempo and beat based on maximum a posteriori (MAP) estimation. Ellis describes a dynamic programming solution for beat tracking by finding the best-scoring set of beat times that reflect the estimated global tempo of music [5]. An extensive evaluation of audio beat tracking and music tempo extraction algorithms, which were included in MIREX'06, can be found in [6].

In the context of multi-modal music and dance analysis towards dance motion synthesis, Shiratori et al. propose a method, which automatically detects the musical rhythm with beat and tempo, performs a music rhythm assisted motion segmentation, and classifies motion segments into the primitive motion units [7]. In an earlier work [8], we have addressed the problem of multi-camera audiovisual analysis of dance figures, where a correlation model between body motion and music is extracted by unsupervised temporal segmentation of the recurrent elementary audio and body motion patterns. Later in [9], we have described an automatic music-driven dance animation scheme based on supervised modeling of music and dance figures in a simplified scenario, where a dance performance is assumed to have only a single dance figure which is to be synchronized with the musical beat.

In this present paper, we propose a complete framework for modeling, analysis, annotation and synthesis of multi-modal dance performances, which can handle more complex and realistic scenarios. Specifically, we focus on finding mappings, which are in general many-to-many, between audio patterns and dance figures for music-driven dance choreography synthesis.

2. MUSIC-DRIVEN DANCE SYNTHESIS FRAMEWORK

The overall framework, as depicted in Figure 1, comprises of several blocks that can be grouped into five main tasks: beat extraction and measure localization; audio feature extraction; measure modeling and identification; dance figure labeling and N-gram modeling; multi-modal dance figure estimation.

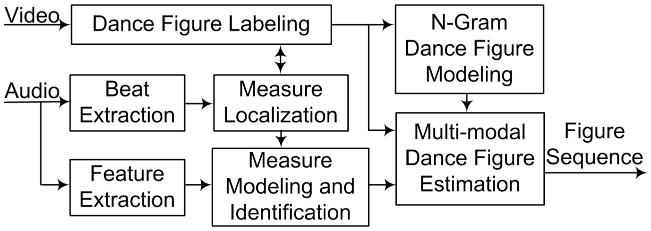

Fig. 1. Block diagram of the overall multi-modal dance performance analysis-synthesis framework.

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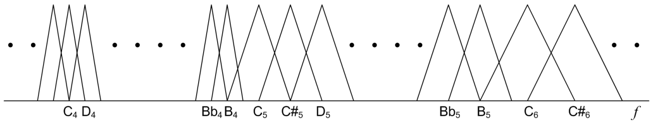


Fig. 2. Triangular overlapping windows centered at the locations of semitone frequencies at different octaves during chroma features extraction.

Audio is processed in two parallel tasks. One of the tasks extracts beat and meter information from audio to determine the measure boundaries whereas the other task extracts features from audio as chroma features. The outputs of this task are used for measure modeling and identification.

On the other hand, video is manually segmented into recurrent dance figures and each dance figure is assigned with a label. The sequence of dance figure labels is then used to calculate the N-gram probabilities so as to capture the underlying figure-to-figure transition structures in the original dance choreography.

For measure modeling and identification, we train HMMs to capture different rhythmic audio patterns that correspond to each dance figure. The trained HMMs are then used in associating each musical measure with a list of likely dance figure ids. The collection of these lists is finally used for dance figure estimation: Given the collection of likely dance figures lists, we estimate a sequence of figure ids based on figure-to-figure transition probability model found by dance figure labeling and N-gram modeling. The following sections explain the aforementioned five main tasks in more detail.

2.1. Beat Extraction and Measure Localization

A musical piece is a collection of measures and a measure is a time segment that is defined as the number of beats in a given duration. Since dance figures are performed in synchrony with musical rhythm, the boundaries of dance figures are expected to match those of the musical measures. For this purpose, we check the accuracy of manually marked dance figure labels by performing measure analysis on music audio. We use one of the recent algorithms proposed by Davies and Plumbey in [10] to extract beats and fine-tune measure boundary locations.

2.2. Acoustic Feature Extraction

Chroma features can be used to characterize the melodic or harmonic content of music since they represent musical audio by projecting the entire spectrum onto 12 bins corresponding to the 12 distinct semitones of the musical octave.

We extract chroma features by following an approach which is very similar to the well-known mel-frequency cepstral coefficients (MFCC) calculation. The difference is in how we choose the triangular overlapping windows while calculating the chroma coefficients from the magnitude spectrum of DFT of the audio signal. We basically center the triangular weight windows at the locations of semitone frequencies at different octaves as shown in Figure 2. Then, we take log-average of the harmonics of the calculated semitone coefficients, that gives us 12-bin chroma features.

2.3. Measure Modeling and Identification

In a dance performance, musical measures that correspond to the same dance figure may exhibit variations and are usually a collection of different rhythmic audio patterns. We employ HMMs to identify and model the audio measure patterns corresponding to the dance figures. Each HMM is trained over the collection of measures co-occurring with the same dance figure. In other words, each HMM computes $P(F|a)$, i.e., probability of dance figure F given a, acoustic chroma features. Hence, we train as many HMMs as the number of different dance figures that exist in the dance performance. Figure 3 shows the HMM structure we use for training models for the collection of measures.

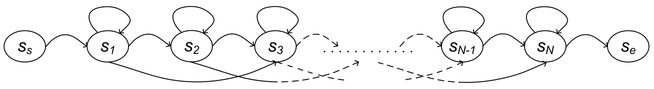


Fig. 3. Left-to-right HMM structure.

For measure identification part of this task, we use the trained HMMs to assign figure ids to the sequence of measures extracted from the input music audio. Instead of identifying each measure with the label of the model that gives the best acoustic score, i.e., the highest likelihood probability of the model match, we create a list of model labels with the highest-N acoustic scores. That is, we generate N alternative transcriptions for each audio frame, i.e., musical measure. We then form a lattice, call it $\mathbf{M}$, where the vertical dimension represents the dance figures and the horizontal dimension represents the frames of music (i.e., measures). The entries of $\mathbf{M}$ are the acoustic scores (i.e., likelihood probabilities) of the corresponding models at the corresponding music frames. This lattice will also be used for dance figure estimation.

2.4. N-Gram Dance Figure Modeling

The N-gram dance figure model provides us with some rules that specify the structure of a dance choreography. For instance, two particular dance figures that never appear in consequence in the training video do not either appear one after the other in the estimated synthesis. We can also enforce a dance figure to always follow a particular figure if it is also the case in the training video with the help of the N-gram model. In this work, we pick $N = 2$ and create a bigram probability matrix, call it $\mathbf{A}$, for the input dance figure sequence to capture the dependency relation of the current dance figure with the previous one. More specifically, each entry in $\mathbf{A}$, namely a_{ij}, is the probability of performing the figure F_j after the figure F_i.

2.5. Multi-modal Dance Figure Estimation

Using the bigram matrix $\mathbf{A}$ (computed as explained in Section 2.4) together with the lattice $\mathbf{M}$ (constructed as explained in Section 2.3), we estimate an output dance figure sequence by finding a path along $\mathbf{M}$ in two different ways. In the first one, we follow the *single best path* along $\mathbf{M}$, i.e., the label sequence that has the maximum total likelihood. In the other one, we follow a path in which we pick the *likely* figure, i.e., the figure that is randomly selected according to a predefined distribution, at each music frame.

We employ a Viterbi algorithm to traverse through the columns of $\mathbf{M}$ using $\mathbf{A}$. Recall that an entry in $\mathbf{M}$, namely m_{ij}, represents the likelihood of figure F_i being performed at music frame j. Let N denote the number of rows in $\mathbf{M}$ (which is also the number of different dance figures); T denote the number of columns in $\mathbf{M}$ (which is also the total number of measure segments); and $\phi_j(t)$ represent the partial likelihood score of performing dance figure F_j at frame t along a single path that accounts for the highest partial likelihood from frame 1 to frame t. This partial likelihood can be computed efficiently using the following recursion:

$$\phi_j(t) = \max_i \{\phi_i(t-1)a_{ij}\} m_{jt}. \tag{1}$$

At time t, each partial likelihood score $\phi_j(t-1)$ is known for all dance figures F_j, hence Equation 1 can be used to compute $\phi_j(t)$ thereby extending the partial paths by one music frame. We also define a structure $\psi_j(t)$ to keep track of the argument which maximizes Equation 1, for each j and t, in order to retrieve the dance figure sequence. The overall algorithm for finding the single best dance figure sequence can be summarized as follows:

1. Initialization:

$$\begin{aligned} \phi_j(1) &= m_{j1}, \quad 1 \le j \le N \\ \psi_j(1) &= 0, \qquad 1 \le j \le N \end{aligned} \tag{2}$$

2. Recursion:

$$\begin{aligned} \phi_j(t) &= \max_i\{\phi_i(t-1)a_{ij}\}m_{jt}, && 2 \le t \le T \\ & && 1 \le j \le N \\ \psi_j(t) &= \mathrm{argmax}_i\{\phi_i(t-1)a_{ij}\}, && 2 \le t \le T \\ & && 1 \le j \le N \end{aligned} \tag{3}$$

3. Termination:

$$\begin{aligned} \Phi &= \max_i\{\phi_i(T)\} \\ \Psi(T) &= \mathrm{argmax}_i\{\phi_i(T)\} \end{aligned} \tag{4}$$

4. Path (dance figure sequence) backtracking:

$$\Psi(t) = \psi_{\Psi(t+1)}(t+1), \quad t = T-1, T-2, \ldots, 1 \tag{5}$$

Even though this procedure is designed for the first synthesis scenario, i.e., picking the *single best path* along $\mathbf{M}$, we can easily modify it for the second synthesis scenario, i.e., picking a *likely path* along $\mathbf{M}$. Instead of picking the maximum in Equation 1, we can randomly pick one of the 'likely' dance figures according to a prespecified distribution P. It is also necessary to update the recurrence relation for $\psi_j(t)$ accordingly.

3. EXPERIMENTS AND RESULTS

In this study, we investigate the Turkish folk dance, *kasik*[1]. Our audiovisual database is 36 minutes long and consists of 20 dance performances with 20 different musical pieces. There are 31 different dance figures (i.e., $N = 31$) and a total of 1265 musical measure segments (i.e., $T = 1265$).

Table 1 provides the distribution of dance figures for different musical pieces (denoted by MP$_1$ through MP$_{20}$ in the first column), showing the many-to-many nature of the mapping between dance figures and music measures. That is, there are different dance figures performed with the same musical piece and some dance figures are performed with more than one musical piece. More importantly, each row in the third column of Table 1 shows the expert-specified group(s) of figures that are alternatives to one another for the corresponding musical piece. For instance, dance figure *a2* can be performed in places where *b2* is performed, or vice versa, with the first musical piece and the change of places between these two figures creates a different but still acceptable choreography according to the expert. This information will be useful in evaluating the output of the dance figure estimation task.

Table 1. List of figures for each musical piece and the corresponding groups of exchangeable figures.

	List of Figures	Exchangeable Figure Groups
MP$_1$	a2, b2, e2, f1, i1, i2, z1, z2	{a2, b2, e2}; {b2, f1, z1}
MP$_2$	b4, e4, h2, z2	{b4, e4, h2}
MP$_3$	b2, e2, f3, h3, i1, i2, o1	{b2, e2, f3, h3, i1, i2, o1}
MP$_4$	b4, e4, f2, h5, o, z1, z2	{b4, e4, f2, h5, o}
MP$_5$	l	
MP$_6$	b2, e2	{b2, e2}
MP$_7$	d, e2, n1, z2	{e2, n1}
MP$_8$	b4, f2, h5, n1, n2, z1	{b4, f2, h5, n2}; {n1, z1}
MP$_9$	e2, n1, o1, z1	{e2, o1}; {n1, o1}
MP$_{10}$	b4, e4, h2, n2, z1	{e4, n2}; {b4, h2}
MP$_{11}$	h5, l, p, x	{h5, l, p, x}
MP$_{12}$	h2, l, x	{h2, l, x}
MP$_{13}$	h3, h6, r, z1, z2	{h3, h6}; {r, h6}
MP$_{14}$	b4, e4, f2, h5, n, o, z2	{b4, f2}; {n, o}
MP$_{15}$	s, t, z2	
MP$_{16}$	f2, h5, n2, o, u, z1	{f2, h5, n2, o}
MP$_{17}$	b2, e2, f3, n1, o1, z1	{b2, e2}
MP$_{18}$	f1, h5, v, y	{f1, h5, v}
MP$_{19}$	b2, e2, f3, z2	{b2, e2, f3}
MP$_{20}$	b2, e2, f3, n1, z1	{b2, e2}; {f3, n1}

We follow 5-fold cross-validation procedure for measure modeling and identification. We create an HMM for each "measure collection" using four fifth of the audio data and use these models to identify the remaining one fifth. We repeat this procedure five times, each time using different parts of the audio data for training and testing. This way, the entire audio data is identified with recognition ids upon which we base our dance figure estimation task as mentioned earlier in Section 2.5.

We define the following five assessment levels to evaluate each figure label F_s in the synthesized figure sequence compared to the respective figure label F_a assigned by the expert:

- $L0$: F_s is marked as $L0$ if F_s matches F_a.
- $L1$: F_s is marked as $L1$ if F_s does not match F_a, but it is in one of the expert-specified exchangeable figure groups together with F_a; i.e., $(F_s, F_a) \in \mathbf{H}$, where $\mathbf{H} = \{(F_i, F_j) \mid F_i \neq F_j; F_i$ *and* F_j *are in one of the expert-specified exchangeable figure groups*$\}$.
- $L2$: F_s is marked as L_2 if F_s does not match F_a, and it is not in one of the expert-specified exchangeable groups together with F_a, either. However, F_s and F_a are performed with the same musical piece; i.e., $(F_s, F_a) \in \mathbf{O} \setminus \mathbf{H}$, where $\mathbf{O} = \{(F_i, F_j) \mid F_i \neq F_j; F_i$ *and* F_j *are performed with the same musical piece*$\}$.
- $L3$: F_s is marked as L_3 if F_s and F_a should not be performed with the same musical piece, and yet, they are exchanged due to a recognition error because the musical pieces with which they are actually performed have similar rhythmic audio patterns; i.e., $(F_s, F_a) \in \mathbf{R} \setminus \mathbf{O}$, where $\mathbf{R} = \{(F_i, F_j) \mid F_i \neq F_j;$ *the entry* (F_i, F_j) *is nonzero in the confusion matrix resulting from measure modeling and identification*$\}$.
- $L4$: F_s is marked as L_4 if it is not marked as one of $L0$ through $L3$.

[1] *Kasik* means *spoon* in English. The dance is named so because the dancers clap spoons while dancing.

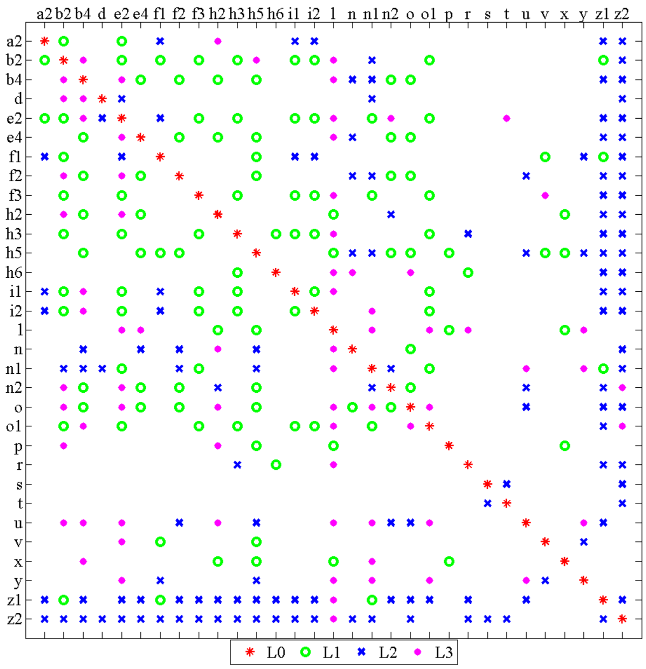
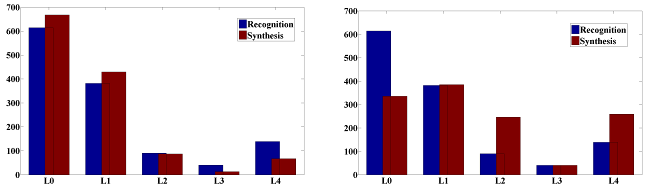


Fig. 4. All assessment levels are put into a single confusion matrix. The empty entries of this matrix correspond to assessment level $L4$.



(a) Synthesis 1

(b) Synthesis 2

Fig. 5. The number of figures that fall into each assessment level for the recognition and the synthesis label sequences in two synthesis scenarios.

Figure 4 displays all assessment levels in a single confusion matrix. We also associate a penalty score ranging from 0 to 4 with the levels $L0$ through $L4$, respectively. Then, we calculate an overall penalty score for measuring the 'goodness' of the resulting dance choreography. Recall that we estimate dance figure sequences in two different ways, as explained in Section 2.5. For both synthesis scenarios, Figure 5 compares the number of figures that fall into each assessment level both for the recognition and the synthesis label sequences. The penalty score for the output figure sequence of the first scenario is 911 whereas it is 2033 for the output figure sequence of the second scenario.

Looking at Figure 5 from another point of view, we see that among all the assessment levels, $L0$, $L1$ and $L2$ are indicators of the diversity of alternative dance figure choreographies rather than being an indicator of error. $L3$ and $L4$, however, can be perceived as indicators of error in the dance choreography synthesis process. In this context, we see that around 94% of the synthesized figures fall into one of the first three assessment levels in the first synthesis scenario. This percentage drops to about 74% for the dance figure sequence of the second synthesis scenario, which is still a high percentage of the entire dance sequence.

In order to visualize the quality of the synthesized choreographies, we created demo videos according to the output dance figure sequences. These demo videos are available online at *http://mvgl.ku.edu.tr/bodymotionanalysis/icassp10/*.

4. CONCLUSIONS

In this paper, we propose a mapping from music measures to dance figures based on correlations between dance figures and music measures as well as correlations between successive dance figures, in terms of figure-to-figure transition probabilities. We, then, use this mapping to synthesize a music-driven sequence of dance figure labels. The output sequence of dance figure labels can be considered as a dance choreography that is in synchrony with the driving audio signal. The experimental results show that the proposed framework is successful at creating *acceptable* alternative dance choreographies.

Possible applications of the proposed framework include: i) an automatic dance tutor that evaluates recorded dance performances of dance students, ii) synthesis of 3D dancing avatars for visual evaluation of synthesized choreographies, and iii) automatic synthesis of dance performances from audio only for on-line games and other entertainment applications, such as 'Second Life'.

5. REFERENCES

[1] A. Hutchinson, *Labanotation: The System of Analyzing and Recording Movement*, Theatre Arts Books, 1977.

[2] Y. Li, T. Wang, and H.-Y. Shum, "Motion texture: a two-level statistical model for character motion synthesis," *ACM Trans. Graph.*, vol. 21, no. 3, pp. 465–472, 2002.

[3] A.P. Ruiz and B. Vachon, "Three learning systems in the reconnaissance of basic movements in contemporary dance," *World Automation Congress, 2002. Proceedings of the 5th Biannual*, vol. 13, pp. 189–194, 2002.

[4] S. Gao and C.-H. Lee, "An adaptive learning approach to music tempo and beat analysis," *Acoustics, Speech, and Signal Processing. Proc. IEEE Int. Conf. on*, vol. 4, pp. 237–240, 2004.

[5] D. P. W. Ellis, "Beat tracking by dynamic programming," *Journal of New Music Research*, vol. 36, no. 1, pp. 51–60, 2007.

[6] M. F. McKinney, D. Moelants, M. E. P. Davies, and A. Klapuri, "Evaluation of audio beat tracking and music tempo extraction algorithms," *Journal of New Music Research*, vol. 36, no. 1, pp. 1–16, 2007.

[7] T. Shiratori, A. Nakazawa, and K. Ikeuchi, "Detecting dance motion structure through music analysis," *Automatic Face and Gesture Recognition, 2004. Proc. Sixth IEEE Int. Conf. on*, pp. 857–862, 17-19 May 2004.

[8] F. Ofli, Y. Demir, E. Erzin, Y. Yemez, and A. M. Tekalp, "Multicamera audio-visual analysis of dance figures," *Multimedia and Expo, 2007 IEEE Int. Conf. on*, pp. 1703–1706, 2007.

[9] F. Ofli, Y. Demir, E. Erzin, Y. Yemez, A. M. Tekalp, K Balci, I. Kiziloglu, L. Akarun, C. Canton-Ferrer, Tilmanne J., E. Bozkurt, and A.T. Erdem, "An audio-driven dancing avatar," *Journal on Multimodal User Interfaces*, vol. 2, no. 2, pp. 93–103, 01 Sep. 2008.

[10] M. E. P. Davies and M. D. Plumbley, "Context-dependent beat tracking of musical audio," *Audio, Speech, and Language Processing, IEEE Trans. on*, vol. 15, no. 3, pp. 1009–1020, 2007.