Journal of Engineering Science and Technology Review 10 (5) (2017) 25 - 32

Research Article

JOURNAL OF
Engineering Science and Technology Review

www.jestr.org

A Virtual Reality Dance Self-learning Framework using Laban Movement Analysis

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Received 14 July 2017; Accepted 30 September 2017

Abstract

The capabilities of general motion evaluation algorithms are significantly limited in analyzing the stylistic qualities and expressions of dance movement. This study proposes a novel dance self-learning framework on the basis of the principles of Laban movement analysis (LMA) to facilitate trainees in automatically analyzing dance movements and correcting dance techniques without an expert. First, a "shape-effort" feature description model was presented in this framework to reflect the subtleties of dance movement. The evaluation of body-shape performance was obtained via open-end dynamic time warping algorithm. Next, rhythm was qualitatively assessed by curve fitting, whereas effort was measured by using standard deviation. Finally, constructive instructions were generated in this framework on basis of the assessment scores of the movement of the trainees. The framework was implemented in cave automatic virtual environment, and its effectiveness and feasibility were verified through experiments. Results demonstrate that the feature description model with 23 LMA parameters can be used in describing dance movements. Multi-mode feedback with direct instructions for the problems in question satisfies the learning habits of the trainee. The quality of the trainees' movements achieves an average of 10% overall improvement by using the framework. Body-shape performance acquires the most improvement of 18%, followed by effort. This study provides a new research method for evaluation and training of dance movements.

Keywords: LMA, dance assessment, dance feature description, dance self-learning framework

1. Introduction

Dancing is an extremely popular activity and is a form of art, where performers use their bodies to convey message and emotions. Individuals might select dance courses in a club or watch videos online to learn the art of dancing. In these dance classes, trainees rely significantly on trainer demonstrations [1] and practice their dance movements through imitation under the close supervision of the trainer. Feedback and advice are provided by the trainer based on the performance of a trainee. Considerable reliance on the trainer is inconvenient and inflexible, although this type of learning is effective. Moreover, learning to dance by watching videos and self-training is a flexible process. However, trainees may not understand every detail of the movements and therefore cannot precisely perform the movements.

The development of virtual reality (VR) technology has enabled researchers to build dance learning systems or dancing games under various 3D virtual environments without actual trainers or their supervisions. This technology has helped trainees overcome the disadvantages of existing learning methods and has facilitated convenient and effective dance learning techniques [2,3,4]. In addition to conventional demonstration function, the trainees' movements in these systems and games can also be compared and evaluated by calculating the differences between the angles of joints of the trainees and the trainers. Then, a considerable feedback is sent to the trainee. However, this type of feedback isn't very helpful for trainees in improving their dance movements given the lack of direct effective instructions. Trainees can only benefit from systems that can systematically evaluate the trainee's movements similar to an actual trainer, highlight inadequacies of their movements, and send constructive feedback and suggestions to improve their movements. However, general movement evaluation algorithms are mainly used in analyzing different types of daily movements, such as running and jumping. These algorithms are inefficient in the analysis of dance movements, including the stylistic qualities and body expressions. Therefore, developing an effective and complete dance movement expression model that can not only quantify the abstract expressiveness in dancing but also extract effort and rhythm features of dance movements has been a constant problem. Simultaneously, a set of novel evaluation algorithms is required to automatically evaluate dance movements in a systematic approach and generate meaningful instructions.

A virtual self-training dancing framework is constructed for the present study under CAVE (cave automatic virtual environment) to solve the above mentioned problem. The trainees' movements are automatically analyzed and evaluated in terms of three aspects, namely, body-shape performance, rhythm, and effort, to effectively evaluate the performance of dance trainees and help them improve.

*E-mail address: gysunlu@gmail.com
ISSN: 1791-2377
doi:10.25103/jestr.105.03

Constructive feedback and comments are generated based on the evaluation results.

2. State of the art

Researchers have conducted an extensive study of dance movement analysis from the perspective of biomechanics, motion observation, and rhythm analysis to analyze the advanced characteristics of dance movements through measurable body features. Therefore, developing an effective movement expression model to achieve improved results for dance movement analysis is crucial. In recent years, Laban movement analysis (LMA) [6] proposed by Rudolf Laban has been used for challenging topics[7, 8], such as analyzing the artistic expressions and emotions of dance movements. Chi et al. [9] proposed using two features of "effort" and "shape" in LMA to control the parameters of the emotional expressions of dance movements; this researcher developed a natural EMOTE system that integrates the target emotions. Masuda et al. [10] added four target emotions, namely, anger, fear, sorrow, and joy, to the basic movements of humanoid robots by modifying the duration, contraction index, momentum, and smoothness of human movements. Truong et al. [11] designed a group of movement descriptors based on LMA and used machine learning framework to identify the movements and emotions of orchestra conductors. However, the movement expression models proposed in the previous studies are incomplete because these studies focus more on certain gestures rather than general dance movements; therefore, these models are unsuitable for characterizing general dance movements. Aristidou et al. [3] designed a movement evaluation algorithm also based on LMA. The algorithm can determine the overall quality of the dance by analyzing the degree of influence of each component of LMA on the dance style. However, the algorithm did not further evaluate the details of the dance movements, and its feedback was not inapplicable to self-training dance trainees.

Rhythm is an important feature of dancing. Researchers have attempted to choreograph dance movements by analyzing the rhythm of the dance. Fan et al. [12] constructed a model that matched dance movements with the rhythm of the music. The model set the extreme point of the variation curve of the human body as the candidate point of the rhythm of the movement. It established a matching relationship between the feature points of the dance movements and of the music by using dynamic time warping (DTW) algorithm. Japanese scholar, Takaaki, [13] acquired the rhythm of the dance by taking samples of music features, such as the starting point, chord change, and drumbeat mode, and applying autocorrelation function. He used this feature to segment dance movements and achieved automatic choreography using the correlations between the rhythm of the movements and the music. Chiang et al. [4] analyzed the mapping relationship between the music and the dance movements by studying the characteristics, such as the melody and volume of the music and the direction of the chord. Therefore, an automatic choreography system was developed based on their findings. However, the focus of the current studies is to study the rhythm of the accompanying music, not of the dance movement. In particular, current studies determine the rhythm of the dance movements through the rhythm of the music.

Researchers also attempted different forms of interactive and evaluation feedback to ensure the effectiveness of the evaluation results in similar self-training dancing system [14, 15,16]. Jacky et al. [2] proposed a framework that first identified dance movement with neural network algorithm and then calculated the movement quality of the different body parts through the DTW comparison algorithm. The results were displayed in scores. Aristidou et al. [3] designed a 3D folk dance learning framework based on their movement evaluation algorithm. This framework helped dancers analyze the overall characteristics of their dance movements; however, the framework did not analyze the details of the movements, such as the style or the setting. In Tai Chi VR teaching system [17], David et al. developed a VR program to simulate Tai Chi exercise courses without offering any instruction or advice. Yang [18] et al. developed a system that could automatically generate course content consistent with the level of the dancer based on his performance. Naemura et al. [19] constructed a learning system that associated the characteristics of the movements, which were extracted from videos, with the rhythms of the dance movements. The association was highly correlated with the subjective evaluation of the skill level of the dancer.

The research results indicate that the systematic evaluation of dancing movements is still limited in the current dancing movement systems. Additional studies on generating direct effective evaluation instructions in the systems should be conducted. Therefore, a movement feature representation model based on the subsets of LMA for "shape-effort" description is first proposed in this study, and the body-shape performance dissimilarity between the movements of trainees and trainers is calculated through the open-end DTW (OE-DTW) algorithm. Then, the curve fitting method is used to extract the basic rhythm of the dance. The effort of the movements is analyzed on the basis of the rhythm of the dance by calculating the standard deviation. Finally, the evaluation results are automatically transformed into direct instructions and sent to the trainees. Dance trainees can benefit from these valuable instructions from the system when the dance trainer is absent.

The remainder of this study is organized as follows. Section 3 presents the "shape-effort" feature description model for dance movement feature explanation and constructs a set of evaluation algorithms to assess body-shape performance, rhythms, and efforts. Section 4 presents the rationality analysis of the framework using the analytical results of the trainee's movements obtained by the system and the analysis of the effectiveness of the learning process of the trainee. Section 5 summarizes the conclusion of the study.

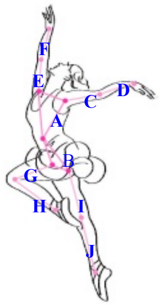
3. Methodology

3.1 "Shape-Effort" Feature Representation Model

LMA is an effective method for the analysis of dance movements. It is divided into four categories, namely, body, effort, shape, and space [6]. The LMA provides a set of valuable and comprehensive parameters that describe the performance and quality of dance movements. The movement feature representation model mainly focuses on describing the shape and effort factors and provides forceful analytical evidence for evaluating dance movements.

3.1.1 Shape

Shape is used to help the trainee understand the movements of a particular part of the body when dancing to satisfy the standard. The body is divided into 10 parts for the purpose of this study. Shape feature parameters are acquired by describing the relations among the 10 body parts. In Fig. 1, the torso is divided into two parts, namely, the upper and lower torso. The other parts include left/right arm, left/right forearm, left/right leg, and left/right foreleg.



A: Upper Torso
B: Lower Torso
C: Left Arm
D: Left Forearm
E: Right Arm
F: Right Forearm
G: Left Leg
H: Left Foreleg
I: Right Leg
J: Right Foreleg

Fig. 1. Illustration of the 10 segments of the body of a dancer

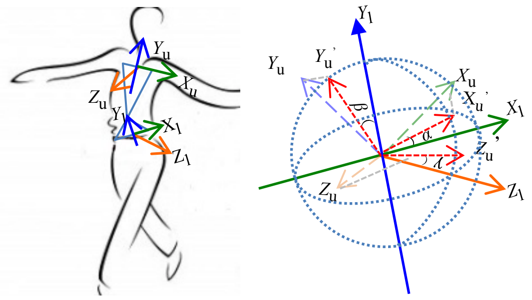


Fig. 2. (a) Upper and lower coordinate systems extracted to depict the torso of the dancer (b) Torso Features

(1) Torso Pattern

In dance performances, dancers often bend, tilt, or twist their torsos in various ways that are different from the movements of the torso in everyday life. In Fig. 2(a), two orthogonal coordinate systems ($\{X_u,Y_u,Z_u\}$ and $\{X_l,Y_l,Z_l\}$) are established respectively to depict the movement of the upper and lower torso. In Fig. 2(b), $\{X_u,Y_u,Z_u\}$ is separately projected onto the X_l-Z_l, X_l-Y_l, and Y_l-Z_l planes to obtain a temporary coordinate system $\{X_u^{'},Y_u^{'},Z_u^{'}\}$. Consequently, the angles $\{\alpha,\beta,\gamma\}$ of the corresponding axis between $\{X_l,Y_l,Z_l\}$ and $\{X_u^{'},Y_u^{'},Z_u^{'}\}$ coordinate systems are set as quantitative indices to represent the torso pattern of a dancer. α (the angle between $X_u^{'}-axis$ and X_l-axis) describes the tilt of the torso, β (the angle between $Y_u^{'}-axis$ and Y_l-axis) describes the twist of the torso, and γ (the angle between $Z_u^{'}-axis$ and Z_l-axis) describes the bending of the torso.

(2) First-Degree Joints

The limbs adjacent to the torso are denoted as first-degree joints, which include the arms and legs. The coordinates of the upper/lower torso, ($\{X_u,Y_u,Z_u\}$ and $\{X_l,Y_l,Z_l\}$), serve as the reference coordinates for the movement of the first-degree joints. This study takes the example of the left arm and mainly uses the inclination and azimuth of the left arm. In Fig. 3(a), *LS* -the left shoulder- represents the joint of the left shoulder, *LE* - the left elbow- represents the joint of the left elbow, and $\overline{(LS,LE)}$ represents the left arm. The angle θ between Y_u-axis and $\overline{(LS,LE)}$ is described as the inclination of the left arm. The angle φ between $\overline{(LS,LE_{XZ})}$ and X_u-axis is calculated to describe the azimuth of the left arm when $\overline{(LS,LE)}$ is projected onto the X_u-Z_u plane. Inclination (θ) and azimuth (φ) of the other three joints are also acquired by adopting the same method.

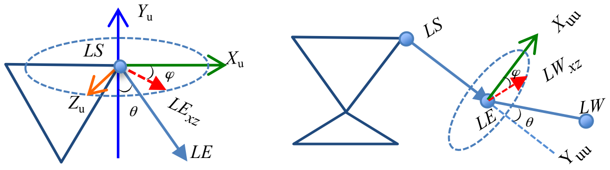


Fig.3. (a) Illustration of the 2D features of a left arm (b) Illustration of the 2D features of a left forearm

(3) Second-Degree Joints

The limbs adjacent to the first-degree joints are denoted as second-degree joints, which include forearms and forelegs. Their inclination and azimuth are acquired by setting up the new Cartesian coordinate system based on their corresponding parent joints. In the case of the left forearm, in Fig. 3(b), the elbow joint is considered the origin point, $\overline{(LS,LE)}$ is $Y_{uu}-axis$, and $X_{uu}-axis$ is the projection of the X_u-axis onto the $X_{uu}-Z_{uu}$ plane which is perpendicular to $Y_{uu}-axis$. $Z_{uu}-axis$ is computed by the cross product of the first two principal components ($Z_{uu}=X_{uu}\times Y_{uu}$). Therefore, the angle θ between $Y_{uu}-axis$ and $\overline{(LE,LW)}$ is used to describe the inclination of the left forearm, and the angle φ between $\overline{(LE,LW_{XZ})}$ and X_{uu} is extracted to describe the azimuth of the left forearm. Similarly, this methodology is applied to the other three second-degree joints.

Thus, the 19 parameters are obtained to describe the main dynamic features of the shape of a dancer. In particular, a complete description of the dynamic changes of the shape of the dance movements is realized by analyzing these parameters. In the following section, these shape parameters are also used to support the output of the assessment advice for the trainee.

3.1.2 Effort

Effort describes the dynamic quality of the movement, feeling tone, texture, and method for exerting energy to each movement. Effort reflects the intention of the dancer toward investing energy in four basic effort factors, namely, flow, time, weight, and space. Each factor varies in intensity that falls between two polarities. The factors are described and quantified as follows:

(1) Weight factor is the resistance of an individual to gravity manifested by increasing (heavy weight) or decreasing pressure (light weight). Weight factor is identified by calculating the deceleration of the hip joint. The movement is light when the curve of the deceleration of the hip joint is smooth. However, sharp curve refers to a strong movement.

(2) Flow factor defines the continuity of the movement. It determines the release (free flow) or control (bound flow) of the movement. Flow factor is measured by calculating the “jerk” (the derivative of the acceleration) of the hip joint. Bound movement has large discontinuities, which are characterized by high jerks, whereas free movement has a slight change in acceleration.

(3) Space factor refers to the attention to space of an individual. It is manifested by either scanning the entire environment (indirect space) or focusing on a single element

(direct space). Space factor is computed by measuring the average acceleration of the hands and feet.

(4) Time factor represents the inner attitude toward time. It is expressed through either sudden time or sustained time. Time factor is estimated by calculating the average velocity of the hands, feet, and hip joints of the performer.

3.2 Professional Assessments

In virtual dance teaching framework, trainees should obtain valuable feedback. The shape, rhythm, and effort of dance movement can be qualitatively assessed by using the OE-DTW algorithm, curve fitting, and standard deviation, respectively, on the basis of the evaluation criteria in traditional dance teaching.

3.2.1 Body-shape Performance Evaluation

The common DTW algorithm is subject to high boundary constraint because the trainee's movements might be incomplete compared with that of the trainer. Therefore, the proposed OE-DTW algorithm discussed in this study computes the dissimilarity (or distance) of the possibly incomplete movement of the trainee by releasing the restrictions of the matching point on the boundary. The result is the smallest value in the last column of the DTW distance table. The OE-DTW algorithm can rapidly calculate the dissimilarity, thus, this algorithm is suitable for real-time feedback learning systems.

1) Posture Dissimilarity

The single posture dissimilarity of the entire body ((postures p_i and p_j) should be normalized using Eq. (1).

$$d_{(p_i,p_j)} = \sqrt{\sum_{k=1}^{N} W_k \left(\frac{f_{i,k} - f_{j,k}}{f_k(\max) - f_k(\min)}\right)^2} \tag{1}$$

where $f_{i,k}$ and $f_{j,k}$ represent the k-th feature parameter of posture p_i and p_j, respectively. $f_k(\max)$ / $f_k(\min)$ are the *max/min* values, and w_k is the weight of the k-th feature parameter. Similarly, the dissimilarity of the parts of the body posture is computed by Eq. (2).

$$d(f_i f_j) = \left[\frac{f_{i,k} - f_{j,k}}{f_k(\max) - f_k(\min)}\right] \tag{2}$$

2) Movement Dissimilarity

$Q = \{p_{q,1} - p_{q,2}, \cdots, p_{q,n}\}$ expresses the trainee's movement, and $R = \{p_{r,1} - p_{r,2}, \cdots, p_{r,m}\}$ expresses the movement of the trainer. The posture dissimilarity matrix between two movements is expressed in Eq. (3). A movement dissimilarity is computed using $D_T(Q,R) = \sum_{l=1}^{L} d_{(p_{q,n_l}, p_{r,m_l})}$, where $T = \{t_1, t_2, \cdots, t_L\}$ and $t_k = (n_l, m_l) \in [1,n] \times [1,m]$

$$\begin{pmatrix} d_{(p_{q,1},p_{r,1})} & d_{(p_{q,1},p_{r,2})} & \cdots & d_{(p_{q,1},p_{r,m})} \\ d_{(p_{q,2},p_{r,1})} & d_{(p_{q,2},p_{r,2})} & \cdots & d_{(p_{q,2},p_{r,m})} \\ \vdots & \vdots & \ddots & \vdots \\ d_{(p_{q,n},p_{r,1})} & d_{(p_{q,n},p_{r,2})} & \cdots & d_{(p_{q,n},p_{r,m})} \end{pmatrix} \tag{3}$$

In the existing DTW algorithm, the movement dissimilarity is the minimum cumulative distance between the two movements. However, the OE-DTW algorithm releases the restrictions of the matching point on the boundary, as displayed in Fig. 4. The result is the smallest value in the last column of the DTW distance table as expressed by the following formula.

$$D_{OE}(Q,R) = \min_{j=1,2,\ldots,m} D_{DTW}(Q,R^j) = D_{T^*}(Q,R^j) = \min\{D_T(Q,R^j)\} \tag{4}$$

The score can be computed by the length of the optimal path L and the result of OE-DTW using $D_{score} = \frac{D_{OE}(Q,R)}{L}$ because of an optimal path L between two movements. The entire body-shape performance or performance of the parts of the body-shape of the trainee can be assessed using this score.

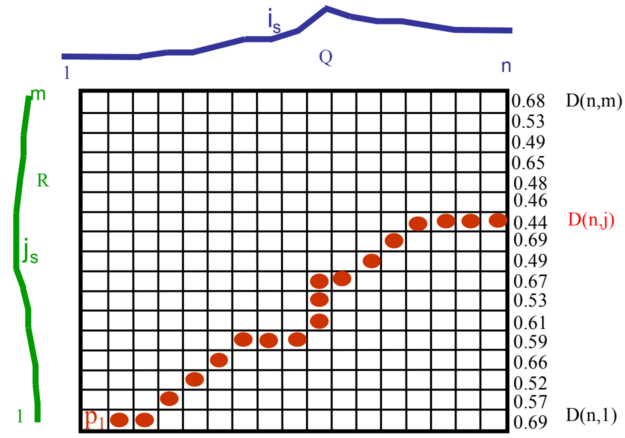


Fig. 4. An OE-DTW algorithm example

The scores can be translated into direct instructions for the parts of the body-shape performance because the range of scores of the body parts reflects the level of the body-shape performance of that particular body part. For example, the score of the tilt of the left arm can be translated into the following feedback.

Table 1. Evaluation Results. Matching incomplete time series with dynamic time warpi

D_{score}	Body Part	Problem Description	Elements Used in Instructions
$D_a^i < D^i < D_b^i$	Left arm	Left arm is lifted slightly high	lower down, slight
$D^i > D_b^i$	Left arm	Left arm is lifted too high	lower down, more
$-D_b^i < D^i < -D_a^i$	Left arm	Left arm is lifted slightly low	lift up, slight
$D^i < -D_b^i$	Left arm	Left arm is lifted too low	lift up,more

3.2.2 Rhythm Evaluation

In a dance performance, the momentum and impulses of the dance movement are typically parallel to the power of the music. Dancers typically reach a special posture at a certain beat; special posture is called "key posture." In the study, the curve fitting analysis algorithm is used to extract the basic rhythm of a dance posture. In Fig. 5, the peak values in each acceleration curve for hands and feet are selected as the candidate points $T = \{t_1, t_2, \cdots, t_n\}$. Then, the cosine curve fitting is applied using the following formula, thereby covering all candidate points.

$$y(t) = \cos(2\pi(\frac{t-t_k}{t_k - t_{k-1}})),\quad t_{k-1} < t < t_k, t_k \in \{T\} \tag{5}$$

A curve that contains the compound rhythm is generated by the weighted average of these cosine curves. The maximum absolute amplitude is considered the intrinsic frequency *f* of the dance movement by using the Fourier analysis, and rhythm is the reciprocal value of *f*, *T=1/f*. The result of the rhythm analysis is presented in the score of rhythm $T_{score} = \frac{T_{trainee} - T_{tranier}}{T_{trainer}}$. Furthermore, the corresponding key postures can also be obtained by searching the best match posture (Eq. 1) around every rhythm point. Table 2 indicates that T_{score} T_{score} can also be converted into direct instructions.

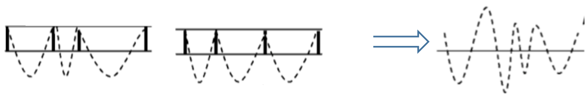


Fig. 5. Curve Fitting Process Example

Table 2. Rhythm Evaluation

T_{score}	Problem Description	Elements Used in Instructions
$T_a < T < T_b$	slightly slow	faster
$T > T_b$	very slow	much faster
$-T_b < T < -T_a$	slightly fast	slower
$T < -T_b$	very fast	much slower

3.2.3 Effort Evaluation

This study refers to the key postures frames of the movement $R_{r,l} = \{k_{r,1}, k_{r,2}, \cdots, k_{r,l}\}$ and divides the entire movement into small segments to evaluate the effort of the dance movement. The duration of each segment is obtained ($t(j) = k_{j+1} - k_j$ and $1 \le j \le l-1$), and the average of every effort factor of the movement of the trainer in each segment is calculated using the following equation.

$$\mu_r(j) = \frac{1}{t(j)} \sum_{i=k_{r,j}}^{k_{r,j+1}} e_{r,i} \tag{6}$$

Then, the standard deviation of the effort factor of the trainee in each segment is computed by Eq. (7).

$$\sigma = \sqrt{\frac{1}{k_{q,1} - k_{q,1}} \sum_{j=1}^{l} \sum_{i=k_{q,j}}^{k_{q,j+1}} (e_{q,i} - \mu_{r,j})^2} \tag{7}$$

The score of each effort factor can be obtained using Eq. (8) after normalization.

$$E_{factor-score} = \frac{1}{k_{q,l} - k_{q,1}} \sum_{j=1}^{l-1} \sum_{i=j}^{j+1} \frac{(e_{q,i} - \mu_r(j))}{\sigma} \tag{8}$$

The effort factors of the trainee can be analyzed respectively based on the $E_{factor-score}$ value, as follows. Corresponding adjustment recommendations can be provided accordingly.

(1) Time factor: The movement is hurried when $E_{time-score} > E_a$; thus, the instruction is "Please slowdown in completing your movement". By contrast, the prompt is "Please rapidly complete your movement" when $E_{time-score} < -E_a$.

(2) Space factor: The force of the movement is extremely violent compared with that of the trainer when $E_{space-score} > E_a$; thus, the instruction is "Please be gentle in completing the movement". By contrast, the prompt is "Please be fiercer in completing the movement" when $E_{space-score} < -E_a$.

(3) Weight factor: The movement is extremely heavy compared with that of the trainer when $E_{weight-score} > E_a$; thus, the instruction is "Please be lighter in completing the movement". By contrast, the prompt is "Please heavily complete the movement" when $E_{weight-score} < -E_a$.

(4) Flow factor: The movement is extremely rigid compared with that of the trainer when $E_{flow-score} > E_a$; thus, the instruction is "Please relax in completing the gesture". By contrast, the prompt is "Please tighten up in completing the movement" when $E_{flow-score} < -E_a$.

4 Result Analysis and Discussion

This study adopts two approaches to test the proposed dance movement evaluation framework. The first approach is to examine the analysis results of the body-shape performance, rhythm, and effort of the dancer during the learning process. The second approach is to test the framework rationality by conducting user research. In particular, trainees are invited to use the system to learn to dance, and the effectiveness of the framework is evaluated by their learning results.

4.1 Building the Framework

In Fig. 6, the dance self-training framework is implemented in a multichannel CAVE. The VR learning environment is constructed by 3D unity engine and serves as the feedback interface. Kinect sensor is used in the framework to collect real-time data on the trainee's movements and applies MiddleVR to control the display of images in CAVE. Three visual feedback modes in Fig. 7, namely, "side-by-side," "overlay," and "score," are set in the framework for the study because the CAVE system is highly immersive and interactive. Trainees can review their own specific dance movement or that of the trainer from a vantage point to identify their problems.

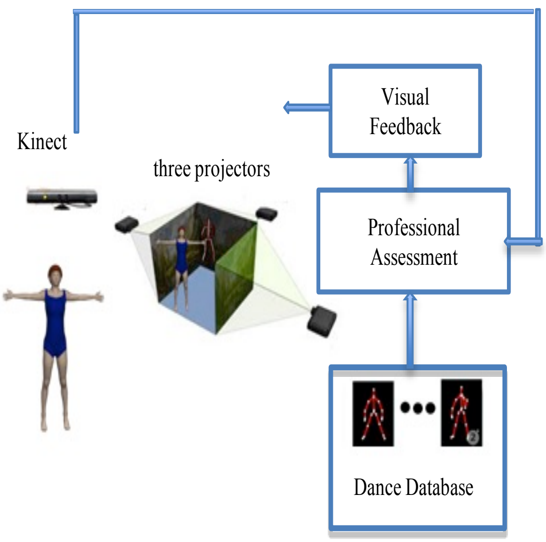


Fig. 6. Framework Architectur

(a)side-by-side mode

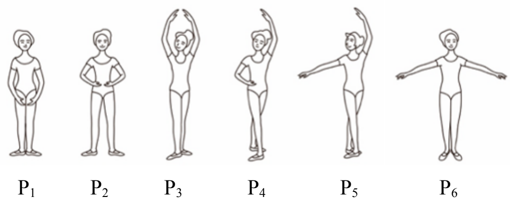
(b)overlay mode

(c)score mode

Fig. 7. muti-mode visual feedback

4.2 Building the Template Movements

The dance movements adopted in the system include the key postures presented in Fig. 8. The standard movements are performed by the dance trainers. Trainee A without experience in dancing and Trainee B with one year experience perform these movements three times. Table 3 illustrates the record of the characteristics of the dance movements, including key postures, duration of the movements, and quality of the movements.



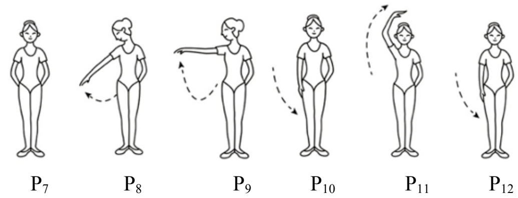


Fig. 8. Key postures Sequence

Table 3. Dance Movement List

Name of the Movement (Quality)	Key Postures
D_{11}(standard), D_{12} (fast, hard), D_{13} (slow, soft)	$P_1 \to P_2 \to P_3 \to P_4 \to P_5 \to P_6$
D_{21}(standard), D_{22} (fast, hard), D_{23} (slow, soft)	$P_1 \to P_2 \to P_3 \to P_4 \to P_5 \to P_6 \to P_7 \to P_8 \to P_9 \to P_{10} \to P_{11} \to P_{12}$

4.3 Dance Movement Evaluation

In the first group of experiments, the study selected the standard pace movement D_{11} from student A with zero dance experience for evaluation. Fig. 9-12 depicts the characteristic curves of the “inclination” and “azimuth” of the left/right arm. The similarity of the shapes of the curves indicates that the trainee’s movement curve bears significant similarity to that of the trainer, and the dance movements are relatively simple. Fig. 13 presents the comparison of key posture frames between the trainee and the trainer. Generally, trainees dance ahead of the beat. The initial movements of the trainee were slightly faster than that of the trainer, whereas the final movements were back on the beat. Fig. 14 illustrates the evaluation scores of the tilt and azimuth of the left/right arm of the trainee. The trainee still showed unstable performance in every key posture, although the movements were not extremely difficult. Fig. 15-16 demonstrates the time and space factors of the trainee’s movements. The inner attitude of her movements was hurried, and the force of the trainee’s movements was unstable.

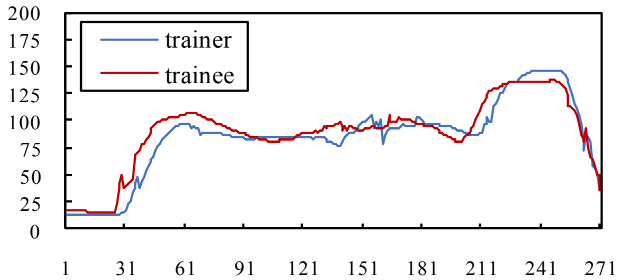


Fig. 9. Feature curves of the left arm tilt

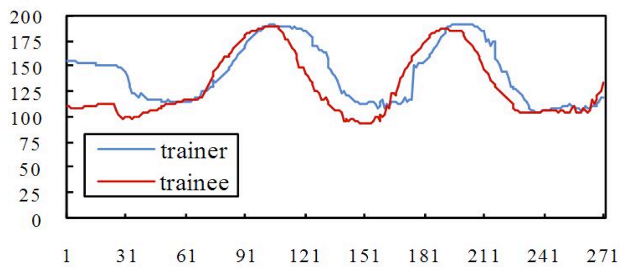


Fig. 10. Feature curves of left arm azimuth

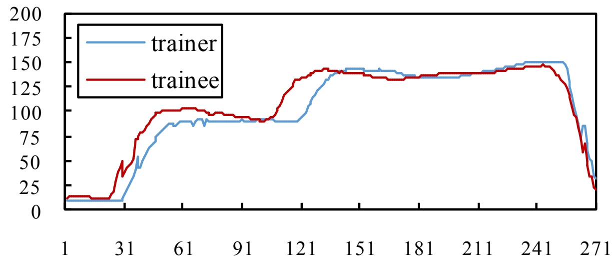


Fig. 11. Feature curves of right arm tilt

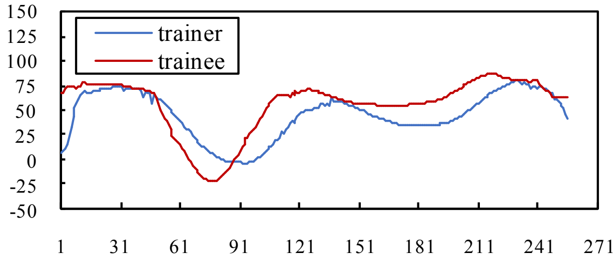


Fig. 12. Feature curves of right arm azimuth

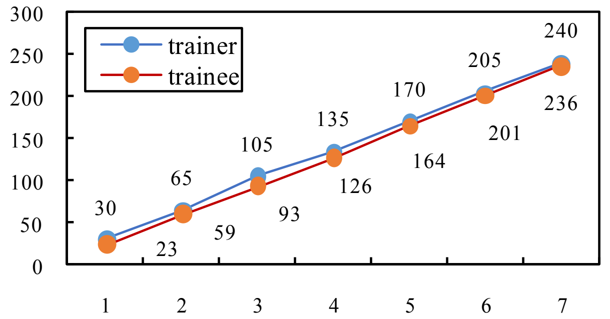


Fig. 13. Key Frame Sequences

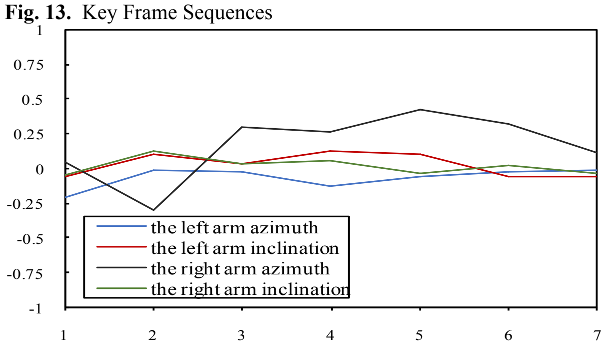


Fig. 14. evaluation score of the left and right arm

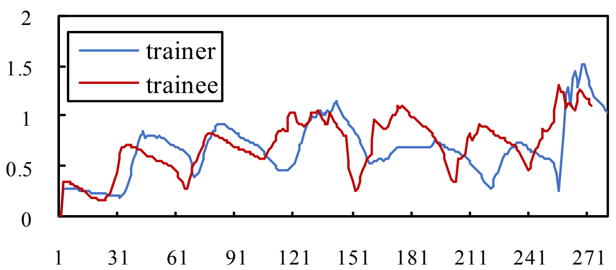


Fig. 15. "time" factor curves

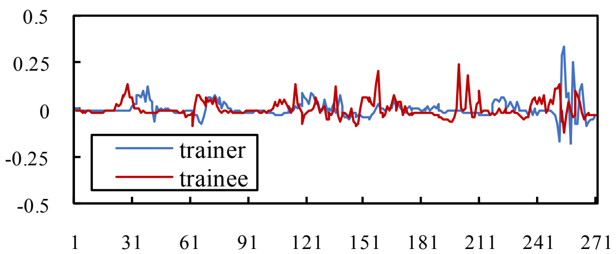


Fig. 16. "space" factor curves

Table 4. Parts of the evaluation score of the trainee

	Shape	Left-arm tilt	Left-arm azimuth	Right-arm tilt	Right-arm azimuth
Body-shape Performance		−0.08	−0.07	0.03	0.14
Rhythm	−0.06				
Space factor	−0.06				
Time factor	0.19				

Referring to the traditional evaluation standards of dance experts, the cut-off points are set as $a=0.1$ and $b=0.3$ for the range of the scores. In Table 4, the framework identifies the most prominent problems of the trainee with the left forearm and rhythm and provides the trainee with feedback, such as "please slowdown in completing your movement" or "please open up your right arm more to complete your movement."

4.4 Learning Effect

The second group of experiments mainly discusses the learning effect of the trainees that use the system. This study uses the movements of two trainees with different dancing experiences. The experiment required the two trainees to perform various dance movements with different degrees of difficulty. Each trainee repeats the movements three times, and the trainee performs adjustments each time based on the feedback provided by the system of the previous performance. The table 5 summarizes the scores of the body-shape performance, rhythm, and effort of the two trainees. Improvements were observed for the two trainees because they repeated the movements.

Table 5 lists the movements of the trainees. Trainee B had learned dancing for a year and performed much better in dance movements at rudimentary Levels 1 and 2, whereas Trainee A with zero dancing experience also performed better at rudimentary Level 1 given that the movements were repeated and simple. However, trainee A showed mediocre performance when the level of difficulty was increased, especially for the fast and strong movement D_{22}. In particular, large deviations appeared in the body-shape performance, rhythm, and effort of the trainee when the movements became difficult. The more experienced trainee showed more steady performance for the same movements with different levels of difficulties, whereas the inexperienced trainee obtained noticeable improvement in the posture factor of D_{22} after absorbing the instructions and feedback provided by the framework. Therefore, a positive correlation exists between the feedback and the improvement of the movement of the dancer. However, neither of the two trainees showed any evident improvement in the rhythm factor after the effort factor was considered, thereby indicating that both trainees did not sufficiently identify the movements.

5. Conclusions

This study reviewed previous studies about conventional dance teaching methods and developed a novel self-training framework based on VR environment to help dance learners evaluate their own dance movement and improve their dancing technique. A shape-effort feature description model and a set of evaluation algorithms were proposed under the novel framework that analyzed and evaluated the dance body-shape performance, rhythm, and effort factors of dance movements and provided direct instructions to the trainees. The following conclusions were drawn:

Table 5. Overall Scores of the Two Trainees

Names of the Trainees and Their Dances	D_{score}			T_{score}			E_{score}		
	N_1	N_2	N_3	N_1	N_2	N_3	N_1	N_2	N_3
A D_{13}	0.23	0.18	0.13	0.13	0.11	0.08	0.22	0.16	0.18
B D_{13}	0.18	0.13	0.22	0.14	0.14	0.15	0.05	0.07	0.13
A D_{12}	0.13	0.08	0.06	0.06	0.04	0.02	0.10	0.13	0.05
B D_{12}	0.11	0.03	0.04	0.08	0.05	0.04	0.12	0.04	0.11
A D_{21}	0.25	0.24	0.19	0.25	0.18	0.12	0.23	0.17	0.11
B D_{21}	0.17	0.12	0.16	0.08	0.12	0.13	0.12	0.17	0.07
A D_{22}	0.35	0.33	0.28	0.34	0.35	0.23	0.38	0.33	0.22
B D_{22}	0.29	0.13	0.23	0.19	0.22	0.18	0.17	0.13	0.08

(1) The shape-effort feature description model based on LMA was effective in the quantitative and qualitative descriptions of dance movements. The model not only quantified the effort factor of the dance movements but also described the body-shape performance and rhythms of the dance movements.

(2) The framework satisfied the dance teaching standard by steadily providing evaluations of the body-shape performance, rhythm, and effort factors of the dance movements.

(3) Evaluation results were transformed into direct instructions and feedback to help learners identify their problems; thus, the system is accessible to self-trainers. In addition, user research suggested that learners achieved discernible improvement in the qualities of their movements after obtaining direct and systematic feedback from the system. The improvement was especially evident at the elementary stage of learning.

In summary, the self-training dance learning framework developed based on the LMA provided dance learners with effective guidance and instruction to improve their dance skills. In the follow-up study, a mapping relationship between the effect of learning and customized teaching content should be established to further improve the system, generate the targeted learning content, and satisfy the specific requirements of each learner. Furthermore, differentiated evaluation standards should be considered in the algorithm because these standards vary for different levels of learners. Thus, the interest of the learner increases, and the effectiveness of the feedback is ensured, thereby making the teaching process personalized.

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