Computer Fraud and Security
ISSN (online): 1873-7056

Dance movement analysis based on big data somatosensory interaction technology

Chenlu Wang[1,*], Yidong Wei[2]

[1]*School of Music, Shaanxi Xueqian Normal University, Xi'an, Shaanxi, China；*

[2]*Innovation Centre Department, Aircraft Strength Research Institute China, Xi'an, Shaanxi, China*

**Corresponding author*

Abstract:

Traditional dance evaluation is mostly carried out through the combination of manual and machine recognition, which can't capture dance movements properly, and can't realize self-evaluation for users who lack manual evaluation conditions. In order to improve the analysis effect of dance movement fluency, this paper proposes a dance movement fluency evaluation system combined with somatosensory interaction technology, and in order to correct the trainer's dance posture, this paper establishes a standard dance movement comparison template. In addition, this paper uses Kinect to collect standard dance movement data, and repairs the occluded joint information to form a standardized movement number. Through the analysis, it can be seen that the dance movement fluency analysis system combined with somatosensory interaction technology proposed in this paper can effectively improve the dance movement evaluation effect. Therefore, applying interactive movements to dance movement analysis is the development direction of dance movement evaluation in the future, and it is also the basis of independent dance learning.

Keywords: somatosensory interaction; dance movement; fluency; data processing

1 INTRODUCTION

As a continuous human movement in a specific time and space, dance expresses the dancer's thoughts and emotions through intuitive human movements and continuous movements, so that the audience can enjoy beauty. This is directly related to the distribution ratio of fluency in dance performances. Smooth and stagnation are important parts of fluency, and any kind of dance performance is inseparable from smooth and stagnation. Meanwhile, the proportion of smooth and stagnation is different in different art forms, so it has different effects. Smooth brings a soft and coherent experience to people, which makes people feel like roaming in the grassland where the wind blows grass and cattle and sheep are low. However, stagnation gives people a compact and intermittent feeling, which makes people feel as if they are in the mountains and mountains. The mutual representation between the two is also opposed to each other, forming a sharp contrast and producing an artistic representation that enriches the dance.

Fluency mainly reveals the freedom and restraint of dancers' psychological level through the smooth or stagnation of movements in the process of human movement, so as to express different emotional catharsis. Dance works promote themes and express emotions through dance movements. Moreover, dance movements are the main part of a dance work and the carrier of emotional expression. Weight, speed, high and low, and smoothness will all form different movement textures. The same movements are expressed through different degrees of fluency. It will also form different meanings [1]. The same movement, when performed with different degrees of fluency, can also form different meanings. Calm and gentle movements performed in a fluent form often appear at the beginning of things or in the development of emotions. However, the contradictions of things and the inner struggles are often expressed in stagnant movements, which form two types of dance movements: dance movements that are mainly fluent or dance movements that are mainly stagnant. However, a complete dance work is often not absolutely smooth or absolutely stagnant, but will reasonably use smooth movements and stagnant movements at an appropriate time point, so that the smooth and stagnant movements can be integrated with each other, and a stagnant sense of shape can be added to the beautiful and smooth movements to achieve a state of dynamic balance. At the same time, stagnation is born from fluency, and smooth is born from stagnation. The two alternate with each other, merge with each other, and promote each other, bursting out strong emotions and profound meanings [2].

This paper establishes a standard dance movement comparison template. In addition, this paper uses Kinect to collect standard dance movement data, and repairs the occluded joint information to form a standardized movement number. Through the analysis, it can be seen that the dance movement fluency analysis system combined with somatosensory interaction technology proposed in this paper can effectively improve the dance movement evaluation effect.

2 RELATED WORKS

(1) Current status of dance movement study

Dance is an art that takes human body movements as its main form of expression. The study of dance optimization is an analysis and evaluation of the fluency, standardization and artistry of movements in the professional field, and its measurement level is deeper and more professional. With the development of science and technology, dance inheritors use videos to record original ecological dance movements. Although the accuracy of training has been improved compared with other forms of recording such as words, there are also angles where videos cannot be captured. In the process of practicing according to the video, the trainer can't observe the dance movements comprehensively, and in the process of practicing according to the video, the trainer lacks feedback information, so the trainer can't have a clear positioning of his own movement level. Moreover, the practice of long-term wrong movements can also cause damage to the muscles of the trainer [3]. Internationally, symbols are used to record dance movements, but symbolic dance recording is very complicated, and dance scores are not like images or pictographic recording methods to give people an intuitive feeling. As a special dance form, original ecological dance has the characteristics of distinctive features and strong expressive force.

With the development of digital media technology, how to better inherit it in digital form is a problem that needs to be solved now. For this reason, scholars at home and abroad have carried out some research work. Reference [4] used MoCap motion capture system to collect dancers' dance movement trajectories in three-dimensional space, and displayed them in combination with VR virtual reality technology, providing a digital platform for future folk-dance inheritance. Reference [5] designed and developed a set of digital dance teaching platform through the skeleton data captured by Kinect, through which trainers can systematically learn hand-waving dance movements and get evaluation after learning. Reference [6] used depth camera to collect the dance movements of standard dancers, and established a standard dance movement library. The trainers performed dance movements in front of the depth camera, and the system automatically collected and recognized the dance movements, compared the standard movements in the movement library, evaluated the trainers' dance postures from two aspects: the angle formed by joints and the coordinates of joint points, and provided movement comparison charts and corresponding guidance suggestions. Reference [7] put forward a gesture sequence segmentation method, which was applied to the recognition of songs and dances to obtain high recognition accuracy.

(2) Pose recognition

Pose estimation technology is an important branch in the field of computer vision. Its goal is to infer the pose information of objects or human bodies by analyzing the input image or video data, including position, direction, angle, etc. In recent years, with the development of deep learning technology, pose estimation technology has made significant progress [8]. Here are some of the latest developments in pose estimation techniques:

Traditional pose estimation techniques are mainly based on two-dimensional images, but in recent years, more and more studies have begun to pay attention to three-dimensional pose estimation [9]. Three-dimensional pose estimation can more accurately estimate the position and direction of objects or human bodies, which is of great significance to virtual reality, robot control and other applications. Meanwhile, traditional pose estimation techniques are mainly aimed at a single object or human body, while multi-person pose estimation needs to consider the interaction and constraint relationship between multiple objects or human bodies. In recent years, more and more studies have begun to pay attention to the problem of multi-person pose estimation [10].

Real-time pose estimation technology is an important problem when it is applied to practical scenarios. In recent years, more and more researches have begun to pay attention to how to improve the real-time performance of pose estimation to meet the needs of practical applications. Generally speaking, the pose estimation technology has matured and its application fields are becoming more and more extensive. In the future, with the continuous improvement of new sensor technologies, machine learning algorithms and computing capabilities, pose estimation technology will have more application and development space [11].

At present, the technology used for human pose detection is developing rapidly, and the accuracy of the algorithm is constantly improving. The excellent frameworks are DensePose proposed by the Facebook Institute [12]. Unlike traditional human pose estimation methods (which only detect key points or joints of the human body), DensePose provides a more detailed and accurate three-dimensional surface representation of the human body. The algorithm proposed in reference [13] is based on deep convolutional neural network, which can handle a wide range of human postures, lighting conditions, and clothing types. The algorithm uses a two-stage process to estimate the dense pose of the human body in the image. First, it detects the rough location of the body parts, and then refines the location and orientation of the body parts by predicting a UV map that maps the 3D surface of the body to the 2D image space.

Real-time detection of 2D coordinates of body joints and body parts (such as head, torso, arms and legs) proposed in reference [14] uses RGB images from a single camera. It can handle multiple people in the same frame of video and can detect up to 135 keypoints per person. Reference [15] used a deep neural network to detect key points, which is trained on a large dataset of annotated human poses.

3 IMPLEMENTATION OF THE SYSTEM

This paper will mainly introduce the realization process of dance interaction from the mode of somatosensory interaction, the realization of virtual scene interface, and the realization of two modules (somatosensory motion module and data processing module).

3.1 Kinect sensor and its composition

The Kinect peripheral contains three cameras, the RGB camera captures color images, and the depth sensor consists of an infrared transmitter on one side and an infrared receiver on the other, which is used to create depth images of people and objects. In addition, the device is also equipped with a quaternary microphone array, which is specially used for background noise filtering, sound source localization and speech recognition and provides rich interactive functions(Figure 1). In addition, other components include built-in motor to automatically adjust elevation angle, power supply, USB cable, etc[16].

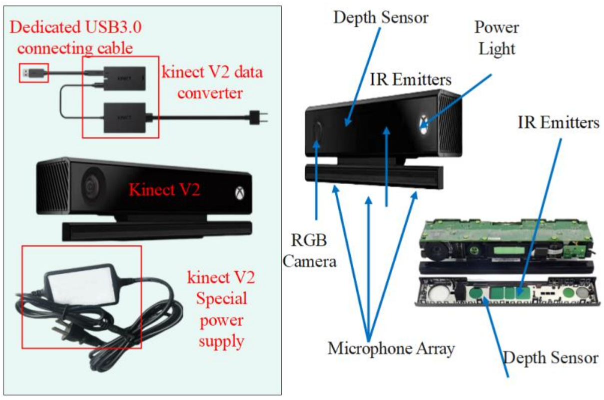
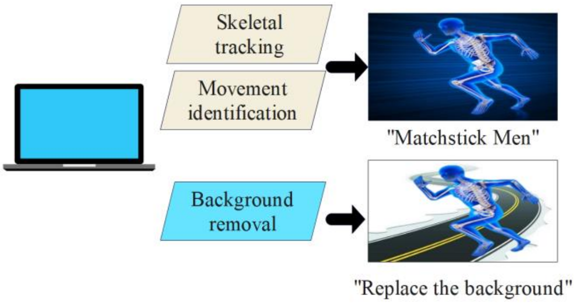
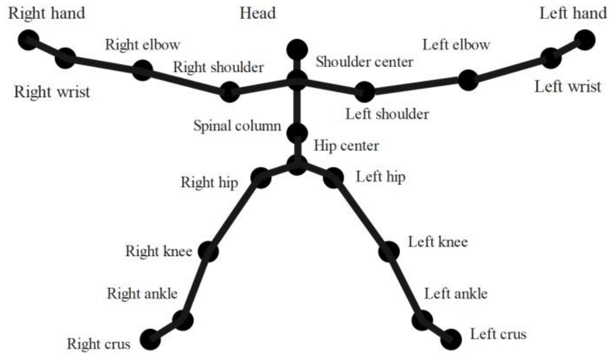


Figure 1 Kinect 2.0 hardware structure

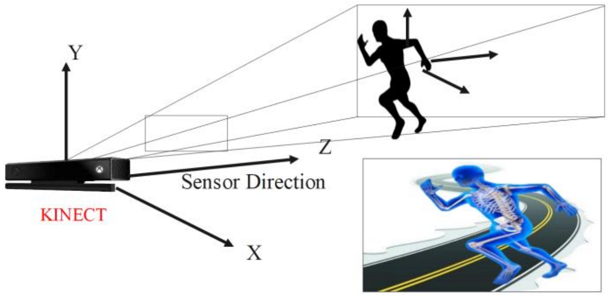
The analysis diagram of three key technologies of Kinect is shown in Figure 2. These technologies provide Kinect with powerful interactive capabilities and greatly expand its application potential in education, entertainment, rehabilitation and other fields. Through in-depth research and optimization of these key technologies, a more efficient, accurate and user-friendly somatosensory motor interaction system for dancers can be developed[17].



(a) Bone tracking



(b) Action recognition



(c) Background removal

Figure 2 Analysis of three key technologies of Kinect

3.2 Implementation of somatosensory motor module

3.2. 1Task1-visual-upper limb movement coordination task implementation

Task 1 Implementation steps of visual-upper limb movement coordination task:

(1) The Kinect device is properly connected and the device is turned on.

(2) The dancer enters the Kinect detection range, and the device begins to track the user's position and movements, and displays the user's image on the screen in real time.

(3) Kinect will automatically ignore non-target users and bone points beyond the predetermined action range in the interface.

(4) The user starts the task with a specific posture and "raises both hands". At this time, the system gives the user a signal to start the test.

(5) Kinect tracks the movement of the upper limb in the user's hand, and converts the tracked three-dimensional coordinates into two-dimensional coordinates on the screen, so that the virtual upper limb movements with the dancer's hand movement.

(6) Dancers interact through the movements of upper limbs, and the system will give scores and feedback according to the accuracy and timing of striking.

(7) It lasts for a certain period of time (such as 60 seconds) or until the user ends the task. In terms of technical implementation, the key formulas needed are to convert the three-dimensional coordinates captured by Kinect into two-dimensional coordinates on the screen, so as to accurately display the upper limb position in real time, convert the three-dimensional coordinates of Kinect into depth image coordinates, and convert the depth image coordinates into color image coordinates. Then, it adjusts the color image coordinates according to the screen size and resolution to ensure that the position of the virtual upper limb on the screen matches the position of the user's actual limb. The specific coordinate conversion formula is[18]:

$$x' = \frac{x}{640} \tag{1}$$

The 3D x coordinate of the Kinect is converted to the formula of screen coordinate x', where 640 is half of the horizontal resolution of the Kinect.

$$y' = 1 - \frac{y}{640} \tag{2}$$

The 3D y coordinate of the Kinect is converted to the formula of screen coordinate y', where 480 is half of the vertical resolution of the Kinect.

These formulas are programmatically implemented in conjunction with the APIs provided by the Kinect SDK to ensure that they can respond to user actions in real time and display them accurately on the screen.

3.2. 2 Task2-visual-lower limb movement coordination task implementation

Task 2 Vision-lower limb movement coordination task implementation steps:

(1) The Kinect device is connected and initialized, the Kinect image, depth, and skeletal tracking streams are set up, obstacle objects are created in the scene, and their initial positions on the screen are set.

(2) Kinect is used to track the position of the user's lower limb bones, especially the position of the legs, and obtain the real-time coordinate data of the user's legs.

(3) The user's leg position captured by Kinect is mapped to the leg movements of the character in the system, and the character's movement is calculated through kinematic algorithms so that the character can simulate the user's jumping or dodging movements.

(4) Dynamic generation and movement of obstacles are performed, and obstacles move in the system according to a predetermined path and speed. The movement of obstacles can be achieved through linear interpolation or other animation techniques.

(5) Collision detection is performed to detect the collision between the user character model and the obstacle in real time. If a collision is detected, the corresponding operation is performed according to the user logic, and no points are awarded.

(6) Every time the user successfully crosses an obstacle, the score is increased. If the user encounters an obstacle, visual and audio feedback is given, and no score is scored accordingly.

The calculation formula of jumping action height is[19]:

$$y(t) = v_{0y} \cdot t - \frac{1}{2} \cdot g \cdot t^2 \tag{3}$$

The formula for calculating the screen mapping coordinates of the dancer's lower limbs is:

$$x_{screen} = scale_x \cdot \left(x_{kinect} - x_{offset} \right) \tag{4}$$

$$y_{screen} = scale_y \cdot \left(y_{kinect} - y_{offset} \right) \tag{5}$$

The update formula for the position of obstacles on the screen is:

$$x_{obstacle} = x_{obstacle}(t-1) - v_{obstacle} \cdot \nabla t \tag{6}$$

3.2. 3 Task3-auditory-limb movement coordination task implementation

Task 3 Auditory-limb movement coordination task implementation steps:

(1) Audio input processing is performed, the Kinect microphone array is used to capture audio input, and the audio is processed using a speech recognition algorithm to detect specific voice commands.

(2) Commands are mapped to actions, and the recognized voice commands are mapped to predefined actions in the system.

(3) The activation motion task is performed. Once the command is recognized, the corresponding action in the virtual environment is triggered.

(4) Feedback and scoring are implemented. Immediate feedback is provided to the user, such as a visual or auditory signal to confirm the action, and the system scores or progress are updated based on the correctness and timing of the dancer's response.

(5) Logic guides the system on how to respond based on correct or incorrect actions, including whether to perform or repeat a task.

Sound command recognition accuracy is[20]:

$$Accuracy = \frac{NumberofCorrect\,Re\,sponses}{TotalNumberofCommandsIssued} \tag{7}$$

Response time calculation is:

$$Re\,sponsesTime = t_{action} - t_{command} \tag{8}$$

Among them, the action time is a time point at which the dancer moves, and the command time is a score based on the response time at the time point at which the sound command is issued.

$$Re\,sponsesTime = t_{action} - t_{command} \tag{9}$$

For the jumping action, the position of the foot can be calculated and determined if it intersects the virtual lower extremity,

$$FootPosition = KinectData \times CalibrationMatrix \tag{10}$$

It is then checked for intersection with lower extremity objects.

$$Inter\,sec\,tion = CheckCollision\left(FootPosition, BallPosition\right) \tag{11}$$

3.2. 4 Task4-balance control task implementation

Task4 balance control task implementation steps

(1) Environment construction: First, it is necessary to create a 3D model of the ski piste in the system development platform (Unity3D), and arrange multiple obstacles on the ski piste.

(2) User control: According to the data of the physical motion capture device (Kinect), the dancer's body movement is synchronized with the movement of the virtual character in the system. The actual position of the dancer captured by Kinect is converted into a virtual position within the system:

$$x_{game} = scale_x \cdot \left(x_{kinect} - x_{offset}\right) \tag{12}$$

$$y_{game} = scale_y \cdot \left(y_{kinect} - y_{offset}\right) \tag{13}$$

Among them, $x_{kinect} y_{kinect}$ is the dancer position coordinate captured by Kinect, $scale_x scale_y$ is the scaling factor, and $x_{offset} y_{offset}$ is the coordinate offset.

The action in the system is determined according to the body action of the dancer, such as jumping, and if $\mathrm{V}y > jump\_thresgold$, it is determined to be a jumping action, wherein

$$\mathrm{V}y = y_t - y_{t-1} \tag{14}$$

y_t and y_{t-1} are the vertical positions of the dancers in two consecutive frames, respectively

(3) Collision detection: The collision detection logic is implemented in the system to judge whether the character controlled by the dancer collides with the obstacle, and give the system feedback (such as point reduction, deceleration, etc.) according to the collision result. Then, whether a collision occurs between the dancer and the obstacle is detected, and if the collision determination is[21]:

$$\left| x_{game} - x_{obstacle} \right| < collision\_radius \tag{15}$$

Then, it is considered that a collision has occurred, where $x_{obstacle}$ is the position of the obstacle and $collision\_radius$ is the collision detection radius. Action recognition: Through Kinect and other devices, the specific movements of dancers (such as jumping, squatting, etc.) can be identified, and these movements can be transformed into evasive movements of characters in the system. The obstacle is controlled to move on the screen. The obstacle position is updated as:

$$x_{obstacle}(t) = x_{obstacle}(t-1) + v_{obstacle} \cdot \nabla t \tag{16}$$

Among them, $v_{obstacle}$ is the speed of the obstacle and ∇t is the time interval.

(4) Score and feedback: A scoring system is set up to record the dancers' performance in avoiding obstacles, and feedback is given at the end of the system.

(5) System logic: The system logic code is written, including the state control of the start, progress and end of the task, as well as the obstacle generation logic and the adjustment of the task difficulty.

3.2. 5 Task5- overall body movement coordination task implementation

Task 5 The overall body movement coordination task (through the humanoid wall of different movements) involves the accurate capture and real-time feedback of the dancer's body movements. The following are the implementation steps[22]:

(1) Various humanoid wall shapes are designed, and each shape corresponds to a specific body posture.

(2) Dancer posture capture: Kinect is used to capture the dancer's overall body movements and record the coordinates of each key part of the dancer's body.

(3) Matching posture with human-shaped wall: The dancer’s real-time posture is matched with the shape of the human-shaped wall using a posture matching algorithm, such as the distance formula[23]:

$$D = \sqrt{\sum \left(P_{body_i} - P_{wall_i} \right)^2} \tag{17}$$

Among them, P_{wall_i} is the coordinate of the corresponding part of the humanoid wall.

(4) Successful passing judgment is performed to determine whether the dancer successfully passes through the human-shaped wall. If $\nabla y > jump\_thresgold$, then the dancer is considered to have successfully passed, where threshold is the preset tolerance value.

(5) Scoring and feedback are implemented, and the dancers are scored based on the accuracy and speed of passing through the human wall. The score calculation formula is[24]:

$$score = base\_points - penalty \cdot D \tag{18}$$

Among them, $base\_points$ is the base score, and $penalty$ is the score reduced by the distance error.

(6) Dynamic humanoid wall generation is executed. Humanoid walls are dynamically generated according to the progress of the task, and the difficulty gradually increases.

4 DANCE MOVEMENT ANALYSIS SYSTEM COMBINED WITH INTERACTIVE TECHNOLOGY

4.1 Architectural design

The overall architecture of the system is shown in Figure 3 below:

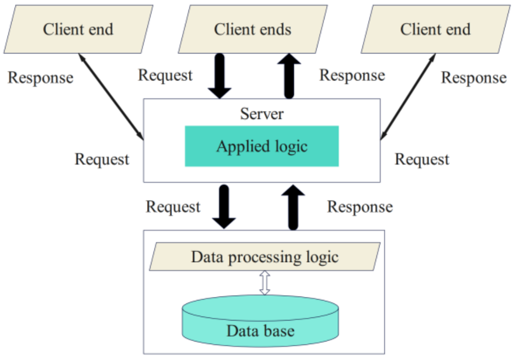


Figure 3 Architecture design

It can be clearly known from the architecture diagram that the relationship between the server and the client is 1 to N, and the server can accept requests from multiple clients for processing at the same time. The database is managed interactively by the server, and at the same time, the purpose of improving the security of the database is achieved.

The design of dance posture intelligent evaluation and correction system is completed according to the idea of quick and simple. Its main functions include the following parts: posture extraction, video alignment, skeleton matching, movement analysis, movement correction, machine learning scoring, message queue management. The overall module structure of the system function is shown in Figure 4.

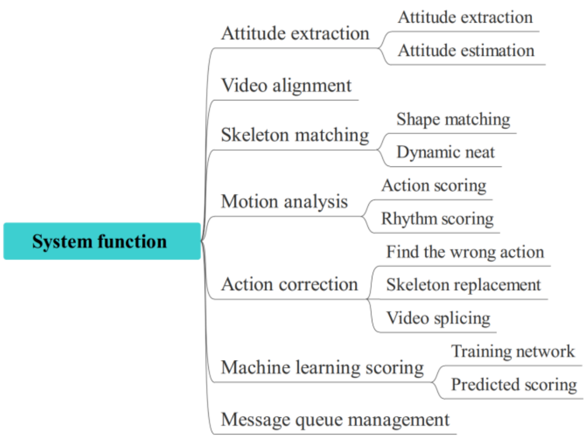


Figure 4 System functional modules

Kinect captures RGB and depth data and transmits them to the underlying API of the software development toolkit SDK for processing, thereby obtaining device information and data flow. This process ensures that the application can receive accurate motion capture information (Figure 5).

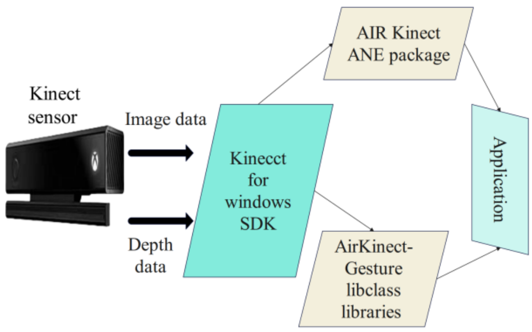


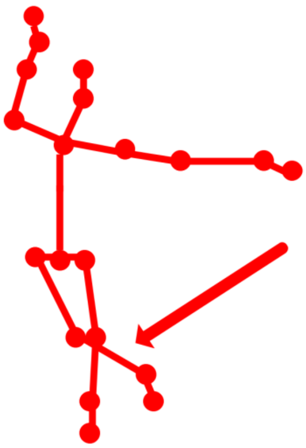
Figure 5 Integration of data flow

According to the previous design and investigation, the system task operation interface and the specific content of each task are determined, and an interactive application based on Kinect is developed by using Microsoft Visual

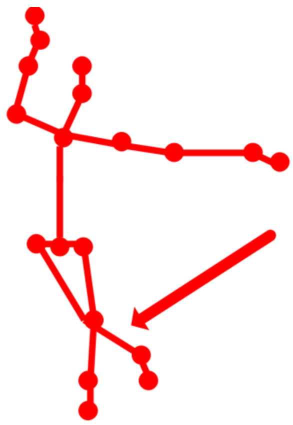
Studio and WPF (Windows Presentation Foundation).

4.3 Results

In order to correct the trainer's dance posture, it is necessary to establish a standard dance movement comparison template. First, Kinect is used to collect standard dance movement data, and the occluded joint point information is repaired to form a standardized movement number. As shown in Figure 6, the white dot is the tracking point. The trainer captures the dance movements of the trainer in real time through Kinect. After preprocessing and repairing the data, the saved data is compared with the data in the template library.



(a) Standard movements



(b) Training movements

Figure 6 Comparison chart of five hand movements

Dance auxiliary training mainly analyzes the position and angle of joint points. The auxiliary system collects the coordinates of joint points of each movement of the trainer, and intuitively finds the differences between movements by comparing them with the movement trajectories of joint points of target movements. Table 1 shows the comparison data of joint coordinates of two movement parts.

Table 1 Comparison of trainer movement and standard movement data

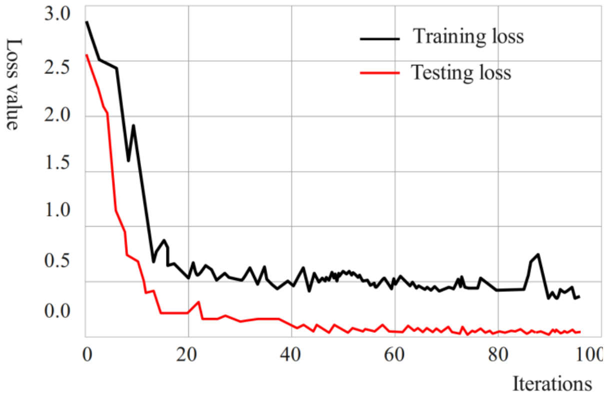
Location	Training joint point coordinates		Standard joint point coordinates	
	Abscissa	Ordinate	Abscissa	Ordinate
Head	-74.69	288.47	-86.24	233.90
Neck	-74.69	79.93	-29.75	34.88
Left shoulder	-223.20	-4.07	-160.82	-54.14
Right shoulder	96.62	-0.96	50.83	543.35
Left Hand	-688.97	-195.60	-704.38	-70.41
Right hand	331.38	399.75	103.15	-8.99
Left knee	-27.39	-906.83	-254.34	-1,020.57
Right knee	-136.64	-882.32	-114.81	-922.98
Left foot	-14.66	-1,072.68	-337.80	-1,227.93
Right foot	-173.98	-1,033.30	-73.62	-1,228.04

The training action information is collected, and the comparison of joint angles is shown in Table 2.

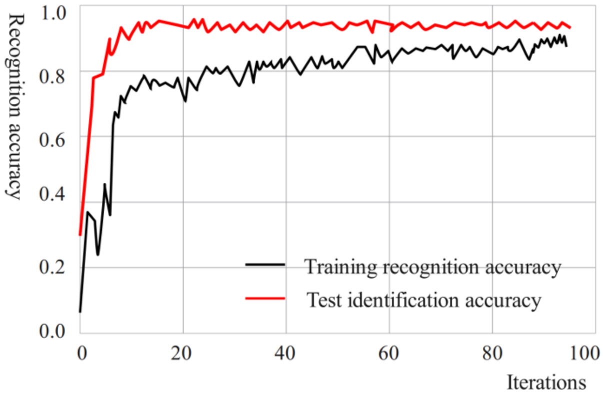
Table 2 Comparison of joint angles

	Trainer	Standard
Right wrist-left elbow-left shoulder	177.68	174.69
Right wrist-left elbow-left shoulder	154.19	110.73
Neck-right shoulder-right elbow	173.45	163.26
Neck-Left shoulder-Left elbow	167.27	175.41
Lumbar-Left knee-Left ankle	163.46	158.31
Waist-right knee-right ankle	163.56	157.38

During the experiment, 3D CNNs are used to train the original ecological dance dataset, and the training-loss curve shown in Figure 7 is obtained.



(a) Training loss



(b) Recognition accuracy

Figure 7 Recognition accuracy and loss function of training set and test set

Then, the algorithm proposed in this paper and classical algorithms such as C3D, P3D, I3D, X3D and ConvLSTM are used to identify the original ecological dance dataset. The experimental results are shown in Table 3.

Table 3 Comparative experimental results

Algorithm	Identification accuracy
T3D	
X3D]	
C3D (1 net)	
I3D	
ConvLSTM	
P3D	
Methods in this paper	

4.4 Analysis and discussion

Whether the movements are smooth or not will be directly displayed, bringing direct visual feelings to the audience. Meanwhile, every dance movement of a dancer is reflected by fluency, which is an indispensable objective existence in dance movements. Dancers have no right to decide whether there is fluency, but they can make different interpretations of fluency. In addition, fluency is very important to dance movements. If we want to thoroughly analyze dance movements, we must study fluency, which shows the importance of fluency to dance.

In this paper, somatosensory interaction technology is used to evaluate and analyze dance movements, and the dance movements are compared with standard movements to judge the fluency of dance movements.

In the somatosensory interactive multi-task motion intervention system, the method for collecting scores by the data processing module generally includes the following steps:

(1) Task execution tracking: The system uses Kinect's bone tracking function to monitor users' actions in performing specific tasks in real time.

(2) Scoring logic programming: According to the task requirements, the system defines scoring rules for each task.

(3) Movement recognition and scoring: The system judges whether the dancer's movements meet the task requirements through a pre-programmed movement recognition algorithm, and gives scores according to the accuracy or speed of the movements.

(4) Summary of results: After each task, the system will automatically calculate and record the total score, and display it on the screen for users to view.

(5) Data storage: The system stores the score of each task on the local database or server for long-term tracking and analysis.

(6) User interface display: On the user interface, scores are usually updated and displayed in real time in the form of numbers, progress bars or charts to enhance users' sense of participation and motivation.

Among them, a specific user action triggers an event for score calculation. These score calculation and data storage functions run in the background without interfering with the user interface interaction of the main program.

According to the comparison of the coordinates of the action joint point in Table 1, it can be seen that there is a large deviation between the coordinates of the trainer's arm and the coordinates of the standard action joint point. It can be seen from Table 2 that compared with the standard movement, the angle of the trainer's right wrist, right elbow and right shoulder is too large, which needs to be corrected according to the time and situation.

Figure 7 shows the loss function of the training set and the test set, where the abscissa is the number of iterations and the ordinate is the loss value. When the number of iterations is 40, the training and loss values begin to stabilize, and the recognition efficiency of the training set is 96%, which is the best training result of the model. After training, save the trained model.

It can be seen from Table 3 that the above seven classical algorithms have achieved high recognition accuracy in the data set of this paper, and the recognition accuracy of this model is higher than that of other classical methods. At the same time, this experiment verifies the rationality of data set collection, feature extraction and the algorithm used in this paper.

Through the above analysis, it can be seen that the dance movement fluency analysis system combined with somatosensory interaction technology proposed in this paper can effectively improve the effect of dance movement evaluation. Therefore, applying interactive actions to dance movement analysis is the future development direction of dance movement evaluation and the basis for autonomous dance learning.

5 CONCLUSION

This paper uses somatosensory interaction technology to evaluate and analyze dance movements, and compares dance movements with standard movements to judge the fluency of dance movements. To correct the trainer's dance posture, a standard dance movement comparison template must be established. Firstly, Kinect is used to collect standard dance motion data, and the occluded joint information is repaired to form a standardized motion number. In pose extraction module, video compression and pose estimation are included, shape matching and dynamic regularization are included in skeleton matching module, motion scoring and rhythm scoring are included in motion analysis module, error finding motion, skeleton replacement and video stitching are included in motion correction module, and training network and prediction scoring are included in machine learning scoring module. The analysis shows that the dance movement fluency analysis system combined with somatosensory interaction technology proposed in this paper can effectively improve the effect of dance movement evaluation. Therefore, applying interactive actions to dance movement analysis is the future development direction of dance movement evaluation and the basis for autonomous dance learning.

For the research and improvement of the somatosensory interactive multi-task motion intervention system, we need to continue to focus on the intervention path of sensory-motor skills, research and develop more dimensions, more enhanced and more effective somatosensory interactive motion intervention, and continue to improve the intervention effect. In addition, we can continue to improve the fun and scene-based improvement to enhance the dancers' sense of participation, immersion and accomplishment.

REFERENCES

[1] Wang, Y. (2022). Research on Dance Movement Recognition Based on Multi-Source Information. Mathematical Problems in Engineering, 2022(1), 5257165-5257177.

[2] Ma, M., Sun, S., & Gao, Y. (2022). Data-Driven Computer Choreography Based on Kinect and 3D Technology. Scientific Programming, 2022(1), 2352024-2352035.

[3] Pang, Y., & Niu, Y. (2023). Dance video motion recognition based on computer vision and image processing. Applied Artificial Intelligence, 37(1), 2226962- 2226970.

[4] Zhao, J. J., Liu, Z. Q., Xie, S. J., & Tang, C. Q. (2023). Research on the application of body posture action feature extraction and recognition comparison. IET Image Processing, 17(1), 104-117.

[5] Zhang, L., Ding, C., Wu, D., Liu, S., & Zhao, Q. (2022). Application of Blurred Image Processing and IoT Action Recognition in Sports Dance Sports Training. Computational Intelligence and Neuroscience, 2022(1), 6189396-6189406.

[6] Kang, L. (2022). A Dance Somersault Pose Recognition Model Using Multifeature Fusion Algorithm. Mobile Information Systems, 2022(1), 3034663-3034672.

[7] Shi, Y. (2022). Stage performance characteristics of minority dance based on human motion recognition. Mobile Information Systems, 2022(1), 1940218-1940230.

[8] Geng, J. (2022). The collection and recognition method of music and dance movement based on intelligent sensor. Computational Intelligence and Neuroscience, 2022(1), 2654892- 2654900.

[9] Gau, M. L., Ting, H. Y., Ting, J. T. W., Peter, M., & Ibrahim, K. (2022). Sarawak Traditional Dance Motion Analysis and Comparison using Microsoft Kinect V2. Green Intelligent Systems and Applications, 2(1), 42-52.

[10] Jin, N., Wen, L., & Xie, K. (2022). The Fusion Application of Deep Learning Biological Image Visualization Technology and Human-Computer Interaction Intelligent Robot in Dance Movements. Computational Intelligence and Neuroscience, 2022(1), 2538896-2538904.

[11] Lei, L., & Tingting, Y. (2023). Reconstruction of physical dance teaching content and movement recognition based on a machine learning model. 3 c TIC: cuadernos de desarrollo aplicados a las TIC, 12(1), 267-285.

[12] Jin, Y. (2022). A Three-Dimensional Animation Character Dance Movement Model Based on the Edge Distance Random Matrix. Mathematical Problems in Engineering, 2022(1), 3212308-3212320.

[13] Sutopo, J., Abd Ghani, M. K., Burhanuddin, M. A., Septiani, A. N., & Tundo, T. (2023). Dance gesture recognition using laban movement analysis with j48 classification. Indonesian Journal of Electrical Engineering and Informatics (IJEEI), 11(2), 528-536.

[14] Chen, J., & Chen, L. (2022). Movement Evaluation Algorithm-Based Form Tracking Technology and Optimal Control of Limbs for Dancers. Mathematical Problems in Engineering, 2022(1), 7749324-7749334.

[15] Kong, Y., & Fu, Y. (2022). Human action recognition and prediction: A survey. International Journal of Computer Vision, 130(5), 1366-1401.

[16] Zhang, L. (2022). Improved Graph Convolutional Neural Network for Dance Tracking and Pose Estimation. Computational Intelligence and Neuroscience, 2022(1), 7133491-7133499.

[17] Iqbal, J., & Sidhu, M. S. (2022). Acceptance of dance training system based on augmented reality and technology acceptance model (TAM). Virtual Reality, 26(1), 33-54.

[18] Ramezanpanah, Z., Mallem, M., & Davesne, F. (2022). Autonomous gesture recognition using multi-layer LSTM networks and laban movement analysis. International Journal of Knowledge-based and Intelligent Engineering Systems, 26(4), 289-297.

[19] Zhang, D. (2022). Analysis of the Style Characteristics of National Dance Based on 3D Reconstruction. Computational Intelligence and Neuroscience, 2022(1), 2419175-2419184.

[20] Feng, M., & Meunier, J. (2022). Skeleton graph-neural-network-based human action recognition: A survey. Sensors, 22(6), 2091-2100.

[21] Sun, D., & Wang, G. (2024). Deep learning driven multi-scale spatiotemporal fusion dance spectrum generation network: A method based on human pose fusion. Alexandria Engineering Journal, 107(3), 634-642.

[22] Kumar, R., & Kumar, S. (2024). A survey on intelligent human action recognition techniques. Multimedia Tools and Applications, 83(17), 52653-52709.

[23] Morshed, M. G., Sultana, T., Alam, A., & Lee, Y. K. (2023). Human action recognition: A taxonomy-based survey, updates, and opportunities. Sensors, 23(4), 2182-2190.

[24] Wang, J. (2024). Research on dance teaching methods based on emotion recognition and emotion analysis. Journal of Electrical Systems, 20(3), 1023-1036.