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Article

Using Augmented Reality to Enhance Immersive Learning Experiences in Dance Education

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Abstract: With the widespread adoption of information technology, the internet, and mobile devices, there has been a significant transformation in learning methods and teaching approaches. In the field of sports dance education, leveraging modern technology to innovate teaching methods and tools can provide richer and more diverse learning experiences while fostering students' comprehensive abilities. This study follows the mechanism by which augmented reality technology enhances dance learning outcomes, utilizing the OpenCV image algorithm library to obtain depth images of dance movements. A random decision forest is employed to classify human body parts, thereby generating a human motion skeleton. Using the obtained data, a dance teaching platform based on augmented reality technology is established. The cosine similarity function is employed to estimate the dance posture of the left arm, for example. By comparing the posture correlation parameters between standard dance movements and the tested dance movements, the mean differences between the two sets of parameters are -0.00154, 0.01537, and 0.00372, indicating that augmented reality technology effectively estimates dance movement postures. A survey was conducted to assess students' satisfaction with the dance education model using augmented reality technology. The mean satisfaction scores for the course, teaching, platform, expectations, perception, and overall satisfaction were 4.3283, 4.4639, 4.0534, 4.4854, 4.4822, and 4.414, respectively, all above 4 points. The course was generally well-received by students, and they expressed a strong willingness to continue learning under this teaching model.

Keywords: OpenCV; Random Decision Forest; Augmented Reality Technology; Dance Instruction

1. Introduction

With the continuous advancement and development of technology, augmented reality (AR) technology has gradually found widespread application across various fields [1-2]. Dance education has also begun to explore and utilize AR technology to create richer, more immersive visual experiences [3-4]. In the field of dance education, the introduction of AR technology has provided learners with more immersive learning experiences, significantly expanding the possibilities of dance education [5-6].

In traditional dance instruction, students typically observe their own dance postures through mirrors or learn dance movements by watching teachers' demonstrations [7-8]. By using AR devices, students can immerse themselves in virtual environments to simulate the learning of various dance movements and performance techniques. This immersive learning experience can stimulate students' interest in learning and enhance learning outcomes [9–11]. They can watch virtual instructors demonstrate movements and adjust their own movements in real time to achieve better dance performance outcomes [12-13]. Additionally, AR technology provides real-time voice guidance and flexible learning methods. By detecting and analyzing students' movements, it offers corresponding guidance and suggestions. Meanwhile, students can choose different scenarios and roles for learning based on their own progress and interests [14-17]. They can repeatedly watch and practice until they achieve satisfactory results. This personalized, interactive, and real-time feedback-based learning approach can better help students understand and master dance and performance techniques, thereby improving learning outcomes [18-21].

Literature [22] highlights the limitations of traditional dance learning (DL) teaching methods and the effectiveness of augmented reality (AR)-driven immersive digital learning environments. By developing AR applications, it demonstrates that AR-driven immersive learning environments can improve dance education. Literature [23] combines AR motion devices with aerobic dance material elements based on self-determination theory and social constructivism to design teaching methods that enhance student performance and motivation. The results indicate that using AR in dance courses can provide a better learning experience and improve students' dance learning outcomes. Literature [24] examines methods for using AI-driven immersive technologies in dance education and analyzes the application of virtual reality (VR), AR, and mixed reality (MR) in dance education, emphasizing that this aids in the development of dance skills and improves teaching practices, thereby enabling the development and improvement of dance skills. Literature [25] highlights the impact of AR technology on the dance field and explores its multifaceted roles in dance, particularly in dance education, emphasizing that AR can effectively promote interactive learning environments, fostering collaboration, creativity, and exploration among students. Literature [26] introduces an AR-based dance training system, noting that this innovative training method can help users adopt a safer lifestyle. It explains that users of this dance training method observe virtual coaches' practice postures from a first-person perspective to receive guidance. Literature [27] conducts a quantitative analysis of the factors influencing user acceptance of AR-based dance training systems (ARDTS), investigating the potential applications of ARDTS in promoting specific dance skills among diverse sample populations with varying backgrounds and interests. The results suggest that ARDTS can facilitate users in acquiring professional dance skills. Literature [28] examines the impact of AR on the experience of watching live dance performances, concluding that AR has a positive effect on stage performance experiences, provided that the content is closely aligned with the performance. Literature [29] developed AR Dancee, a mobile-driven intervention combining AR, machine learning, and persuasive technology, aimed at improving adults' emotions, and the study demonstrated its effectiveness in improving participants' emotions. Literature [30] analyzed how VR supports emotional expression and movement design in dance environments, presenting insights from action research centered on control, collaboration, auditory, and visual feedback, and finally discussed the supportive significance of immersive expression in dance.

This paper categorizes the mechanisms through which augmented reality technology enhances the effectiveness of dance learning into three aspects: immersive visual and auditory experiences, motion capture and real-time feedback, and personalized learning path design. Digital processing of dance movement images is performed to establish an OpenCV image algorithm library, enabling real-time processing of dance movement images. Camera calibration methods are employed to describe dance movement image parameters through effective imaging models, followed by parameter calculation. The core of the Kinect joint tracking algorithm is analyzed, and a random decision forest algorithm is used for human body part classification. Based on the recognition results, the MeanShift algorithm is applied to aggregate pixel points in the body part regions into skeletal nodes, thereby obtaining dance movement data. Using a dynamic sampling light projection algorithm, the three-dimensional model of human movement is reconstructed in depth, and texture mapping is used to complete the realistic modeling of the three-dimensional human model. Based on the needs of dance education, a real-time sports dance movement digital teaching platform based on augmented reality technology is established and applied to immersive dance education.

2. Using Augmented Reality Technology to Enhance the Dance Learning Experience

2.1. The Specific Role of Augmented Reality Technology in Dance Education

2.1.1. Augmented Reality Technology

Augmented reality (AR) technology is a computer-generated simulated environment that enables users to immerse themselves in a virtual space entirely distinct from the real world [31]. In recent years, this technology has seen rapid development, offering users increasingly immersive experiences that expand their perceptual capabilities, allowing them to perceive diverse elements of wonder in a virtual, limitless world. AR technology possesses the following characteristics: first, immersion. AR technology provides sensory stimulation, making users feel as though they are truly immersed in a virtual environment. By wearing a head-mounted display or using other AR devices, users can experience three-dimensional visuals, stereoscopic sound, haptic feedback, and other sensory stimuli, immersing themselves in a realistic environment. Second, interactivity. Augmented reality technology emphasizes user interaction with the virtual environment. Users can interact with the virtual environment through controllers, gesture recognition, and other methods. This interactivity allows users to actively participate in the virtual world and operate and explore it according to their own preferences. Third, customizability.

Augmented reality technology offers high customizability, enabling development tailored to user needs. Both developers and users can customize software and hardware configurations to create augmented reality environments suited to their specific requirements. In summary, the rapid development of augmented reality technology has provided us with a new way of experiencing the world, allowing people to enter a virtual, limitless world beyond the real world and deepen their understanding and recognition of the real world. At the same time, the widespread application of augmented reality technology also brings new challenges. Therefore, to better utilize it, we need to actively address these challenges to fully leverage its advantages while mitigating its disadvantages.

2.1.2. The Specific Role of AR Technology in Dance Education

(1) Provide authentic and intuitive experiences

In college dance practice teaching, teachers often adopt a “demonstration-imitation” model, resulting in monotonous and uninteresting teaching content. Additionally, since teachers tend to focus on demonstrating difficult movements during demonstrations, this can lead to disconnects, making it difficult to provide students with authentic, intuitive experiences. With the assistance of augmented reality technology, teaching content can shift toward being more authentic and intuitive, which not only helps stimulate students' interest in learning but also enables them to better understand and experience dance art. Virtual reality technology can record the postures and movement trajectories of dance performances, helping students better understand their own dance movements and postures, thereby improving the effectiveness of teaching. Additionally, augmented reality technology can create interactive teaching environments for students, encouraging them to engage more deeply in dance practice. Students can also conduct self-directed practice and learning based on their own progress, which helps deepen their understanding of dance and genuinely enhances their proactive participation in dance education.

(2) Creating an immersive teaching environment

The more focused students are during learning, the better the learning outcomes. To enhance students' concentration, it is not only necessary for students to make efforts to improve their focus but also to invest in creating an appropriate teaching environment. Augmented reality technology can be used to create an immersive teaching environment, providing students with a realistic objective world that evokes a sense of presence. This stimulates students' senses in a virtual setting, triggering intellectual resonance and emotional connection, allowing them to focus solely on experiencing the essence of dance and learning dance movements. To elaborate, when students wear augmented reality devices, they can stand directly on the stage, which is adorned with dazzling lights and various stage equipment. This allows students to feel as though they are performing on stage while learning dance, thereby significantly increasing their enthusiasm and focus. An immersive teaching environment is not about students performing alone; it incorporates interactive elements such as teacher guidance and student feedback. This requires teachers to integrate these elements into the virtual environment. For example, when students struggle with certain dance movements, teachers can demonstrate the correct movements step by step and engage in real-time communication with students during the guidance process, thereby providing more targeted instruction.

(3) Real-time evaluation of practical teaching outcomes

Timely and appropriate teaching evaluations help teachers and students identify shortcomings and make swift corrections and adjustments. However, real-time evaluations often pose significant challenges in actual teaching scenarios. Augmented reality technology can facilitate real-time evaluations, thereby driving further optimization and improvement of university dance education.

First, augmented reality technology can integrate both formative and summative evaluations in university dance education, breaking away from the traditional evaluation method centered on end-of-term assessments and ensuring the comprehensiveness of dance education evaluations. Specifically, augmented reality technology can capture three-dimensional, panoramic, and continuous performance records in real time, which can be played back at any time, enabling teachers to observe students' performance details more comprehensively and deeply, and accurately evaluate their performance. Additionally, this real-time recording and playback functionality enables students to reflect on their performance processes, encouraging them to continuously improve and enhance their dance techniques and expressive abilities. Secondly, augmented reality technology can achieve precision and accuracy in university dance education evaluation, ensuring the reliability of dance education evaluation. This enables teachers to more precisely understand students' dance learning progress and comprehensively grasp classroom teaching progress and effectiveness, laying the foundation for teachers to innovate teaching methods, update teaching approaches, and supplement and optimize teaching content. Specifically, sensors and intelligent algorithms can be used to analyze student performance data in real time.

2.2. Mechanisms for Enhancing the Effectiveness of Sports Dance Learning through Augmented Reality Technology

2.2.1. Immersive Visual and Auditory Experience

Augmented reality technology significantly enhances the effectiveness of sports dance learning through a comprehensive visual and auditory experience. First, the comprehensive visual experience is achieved through a 360-degree perspective and real-time interaction. Learners wearing VR headsets can freely observe their surroundings in a virtual environment, experiencing an immersive sensation indistinguishable from the real world. The 360-degree perspective allows learners to examine their movements from multiple angles, enabling them to promptly identify and correct errors in their movements. Real-time interaction technology enables learners to interact with objects or characters in the virtual environment, further enhancing the realism and enjoyment of practice. Additionally, the application of high-fidelity sound effects plays a significant role. High-quality sound effects not only provide realistic musical backgrounds but also adjust in real time based on the learner's movements, enhancing rhythm and coordination. Through dual immersion in both visual and auditory experiences, learners can focus more intently on dance practice, improving the accuracy and expressiveness of their movements, thereby significantly enhancing overall learning outcomes.

2.2.2. Motion Capture and Real-Time Feedback

Motion capture and real-time feedback are one of the key mechanisms through which augmented reality technology enhances the effectiveness of sports dance learning [32]. The use of motion sensors and motion capture technology enables precise recording of every subtle movement made by learners. By wearing sensors on key parts of the body, the system can capture the learner's movement trajectories in real time and convert them into corresponding actions in the virtual environment. This not only allows learners to see their movements in the virtual world but also enables them to identify areas for improvement by comparing their movements with standard movements. Real-time feedback and correction mechanisms are key to enhancing learning outcomes. The system can provide real-time feedback based on captured motion data, identifying incorrect or improper movements and offering corrective suggestions. This immediate feedback mechanism significantly reduces the time required to correct errors, enabling learners to improve quickly and enhance the accuracy and fluidity of their movements. Through motion capture and real-time feedback technology, augmented reality systems can provide learners with efficient and precise practice guidance, significantly enhancing the effectiveness of sports dance learning.

2.2.3. Designing Personalized Learning Paths

The design of personalized learning paths is another key mechanism through which augmented reality technology enhances the effectiveness of sports dance learning. Based on learners' skill levels and needs, the augmented reality system can provide customized training plans tailored to learners of different proficiency levels. Beginners can start with basic movements and simple dance steps, gradually progressing to more complex dance combinations, while experienced dancers can directly move on to training for high-difficulty moves. The system can also offer diverse dance styles and practice content based on learners' interests and strengths, meeting their personalized needs. Tracking and evaluating learning progress is a key method for achieving personalized learning. The augmented reality system records learners' practice data and progress, tracks learning progress in real time, and generates detailed assessment reports. These reports not only include metrics such as movement accuracy, rhythm, and coordination but also identify learners' weak areas through data analysis and provide targeted improvement suggestions. This personalized learning path design not only enhances learners' learning efficiency but also boosts their confidence and interest in learning, thereby achieving better learning outcomes.

3. Dance Education Based on Augmented Reality Technology

3.1. Digital Image Processing of Dance Movements

3.1.1. OpenCV Image Algorithm Library

OpenCV is a rich, open-source, cross-platform computer vision algorithm library with excellent portability, containing a wide range of computer vision-related algorithms for rapid image processing. Starting from version 2.x, it is implemented using the C++ programming language while remaining compatible with the data structures and interface functions of version 1.x, which were based on the C language. OpenCV includes multiple shared libraries or static libraries, such as calib3d, contrib, core, imgproc, features2d, flann, ml, and many other modules. All code within the library is optimized for real-time image processing.

3.1.2. Camera Calibration

Camera calibration is the foundation of machine vision technology, aiming to establish an effective imaging model to describe the physical properties of the camera being used, determine camera parameters, and restore the correspondence between real-world 3D spatial points and 2D image pixels in the camera model. Among these, camera internal parameters are solely determined by the physical properties of the camera itself, including the parameter matrix, three radial distortion parameters, and two tangential distortion parameters. Camera external parameters represent the position and orientation of the camera in the world coordinate system, which are determined by the relative pose relationship between the camera and the world coordinate system.

In computer vision, there are typically three distinct coordinate systems: the world coordinate system, the camera coordinate system, and the image coordinate system, as shown in Figure 1, represented by $X_wY_wZ_w$, xoy, and $X_fO_fY_f$, respectively. The world coordinate system is the absolute coordinate system of the real objective world. The camera coordinate system is a three-dimensional Cartesian coordinate system established with the focal center of the camera model as the origin and the camera optical axis as the z axis, where xy is generally parallel to the image pixel coordinate system XY. The image coordinate system is typically divided into two types: the image pixel coordinate system, which uses pixels as units, and the image physical coordinate system:

(1) Image physical coordinate system: Its origin is the intersection of the lens optical axis and the image plane, with coordinate axes parallel to the camera coordinate system, and units in millimeters.

(2) Image pixel coordinate system: A plane Cartesian coordinate system fixed to the image and based on pixels, with its origin at the top-left corner of the image.

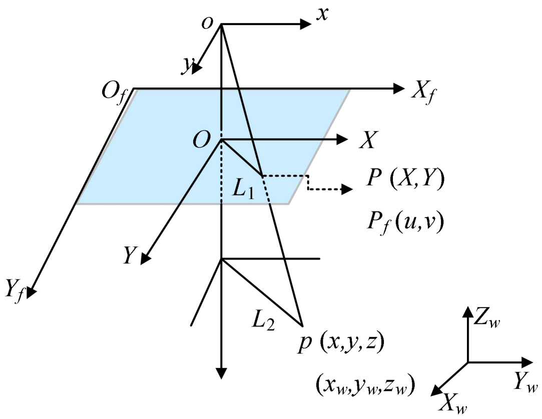


Figure 1. The coordinate system commonly used in camera calibration.

The transformation formula for converting a point in the world coordinate system to the camera coordinate system is shown in (1) below:

$$\begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix} = \begin{bmatrix} R & T \\ 0^T & 1 \end{bmatrix} \cdot \begin{bmatrix} x_w \\ y_w \\ z_w \\ 1 \end{bmatrix} = \begin{bmatrix} r_{11} & r_{12} & r_{13} & t_x \\ r_{21} & r_{22} & r_{23} & t_y \\ r_{31} & r_{32} & r_{33} & t_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_w \\ y_w \\ z_w \\ 1 \end{bmatrix} \tag{1}$$

R and T are the external parameters of the camera. T is the coordinate of the origin of the world coordinate system in the camera coordinate system, and matrix R is an orthogonal rotation matrix that satisfies the constraint conditions:

$$\begin{cases} r_{11}^2 + r_{12}^2 + r_{13}^2 = 1 \\ r_{21}^2 + r_{22}^2 + r_{23}^2 = 1 \\ r_{31}^2 + r_{32}^2 + r_{33}^2 = 1 \end{cases} \tag{2}$$

The coordinates of a point p in the camera coordinate system are:

$$\begin{cases} X = f_x / z \\ Y = f_y / z \end{cases} \tag{3}$$

Its homogeneous coordinate system is expressed as:

$$z\begin{bmatrix} X \\ Y \\ 1 \end{bmatrix} = \begin{bmatrix} f & 0 & 0 & 0 \\ 0 & f & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}\begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix} \tag{4}$$

Further convert the physical coordinate system in the above equation into an image coordinate system:

$$\begin{cases} u - u_0 = \dfrac{X}{d_x} = s_x X \\ v - v_0 = \dfrac{Y}{d_y} = s_y Y \end{cases} \tag{5}$$

In this context, u_0 and v_0 represent the center coordinates of the image, while d_x and d_y denote the physical dimensions of a pixel along the X and Y axes, respectively. $s_x = 1/d_x$ and $s_y = 1/d_y$ correspond to the sampling frequencies along the X and Y axes, respectively, i.e., the number of pixels per unit length. Therefore, the transformation relationship between the object point p and the image point p_f in the image pixel coordinate system is:

$$\begin{cases} u - u_0 = fs_x x / z = f_x x / z \\ v - v_0 = fs_y y / z = f_y y / z \end{cases} \tag{6}$$

$f_x = fs_x$ and $f_y = fs_y$ are defined as the equivalent focal lengths in the X and Y directions, respectively. The four parameters f_x, f_y, u_0, and v_0 are related only to the internal structure of the camera and are internal parameters of the camera.

Transformation relationship between the world coordinate system and the image coordinate system:

$$\begin{cases} \dfrac{X}{f} = \dfrac{u - u_0}{f_x} = \dfrac{r_{11}x_w + r_{12}y_w + r_{13}z_w + t_x}{r_{31}x_w + r_{32}y_w + r_{33}z_w + t_z} \\ \dfrac{Y}{f} = \dfrac{v - v_0}{f_y} = \dfrac{r_{21}x_w + r_{22}y_w + r_{23}z_w + t_y}{r_{31}x_w + r_{32}y_w + r_{33}z_w + t_z} \end{cases} \tag{7}$$

Converted to homogeneous coordinates:

$$z\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} f_x & 0 & u_0 & 0 \\ 0 & f_y & v_0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}\begin{bmatrix} R & T \\ 0^T & 1 \end{bmatrix}\begin{bmatrix} x_w \\ y_w \\ z_w \\ 1 \end{bmatrix} = M_1 M_2 X = MX \tag{8}$$

The above formula is the mathematical expression of the pinhole model or central projection. Using several known object points and corresponding image pixel coordinates, the internal and external parameters of the camera can be calculated.

3.2 Core of Kinect Joint Tracking Algorithm

3.2.1. Deep Image Acquisition

Kinect projects infrared light using an infrared projector and receives it using an infrared camera, with the projection and reception areas overlapping.

Infrared cameras can generally be divided into two categories:

(1) Time-of-Flight (ToF) cameras, which calculate depth information by measuring the transmission delay between light pulses. The device first emits a pulse of light, which is reflected by the object and received by the receiver. The distance to the target is calculated by measuring the time difference. This technology is highly accurate but comes at a significant cost.

(2) Structured light measurement, a type of depth camera based on optical encoding technology. By projecting encoded infrared light into the scene and capturing it with another CMOS image sensor, depth information is determined. This technology is widely adopted due to its relatively low cost, fast processing, portability, and high precision.

3.2.2. Human Body Part Classification Based on Random Decision Forests

Figure 2 shows the random forest algorithm.

(1) Obtain the training dataset: Machine learning requires a large amount of input data, so a large number of human subjects with different physical characteristics, such as height and body type, are needed for training. Unlike color images, the training dataset used by Kinect consists of human depth images, which eliminate the effects of texture and color caused by factors such as clothing, skin, and hair. Therefore, a large number of test subjects are arranged to perform random pose changes in front of the depth camera. The system groups the test subjects based on their specific characteristics and stores them in a dedicated image database. To eliminate similar poses and reduce redundant learning by the classifier, the distance formula between two pose maps p_1 and p_2 is defined as (9):

$$f = \max_i \left\| p_1^i - p_2^i \right\|^2 \tag{9}$$

In this formula, i represents the joint number in the human depth map. The maximum Euclidean distance between corresponding joints is defined as the pose distance. When it is less than the set threshold, the two pose images are judged to be similar and are classified as the same pose.

(2) Feature values are extracted from the depth image: Kinect defines the feature value of a specific pixel x as shown in formula (10) below:

$$f_\theta(I,x) = d_I\left(x + \frac{u}{d_I(x)}\right) - d_I\left(x + \frac{v}{d_I(x)}\right) \tag{10}$$

Using the depth gradient as the feature value, where $d_I(x)$ represents the depth value of pixel x in depth map I, and $\theta(u,v)$ describes its offset in the u and v directions. The offset is normalized by $1/d_I(x)$ to ensure that the magnitude of the offset distance does not affect the feature value. This formula intuitively reflects the local relative position and edge relationships of a pixel. To improve pixel-by-pixel computation speed, developers optimized the process using GPU parallel computing technology DryadLINQ and distributed computing methods.

(3) Training and recognition: Kinect uses random decision forests for training and recognition of human body parts, which are composed of numerous unrelated decision trees. Random forests organize a large number of analysis results into decision trees that can efficiently classify and recognize various parts of the human body, improving overall classification accuracy and speed. The classification results of the random forest algorithm are obtained by each decision tree through voting or averaging, which effectively improves decision accuracy.

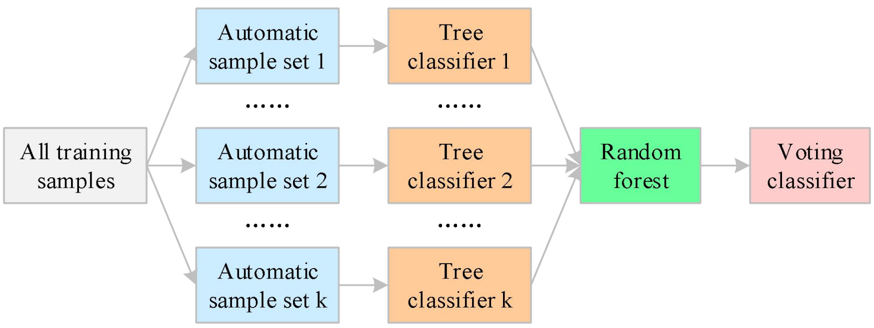


Figure 2. Random forest.

In Kinect, first, a random forest composed of numerous decision trees is trained offline using a large amount of sample data. Each decision tree consists of leaf nodes and branch nodes, with branch nodes comprising thresholds and feature values. The essence of a decision tree is to partition the result space using hyperplanes, ensuring that each leaf node falls within a non-overlapping region of the space. When making decisions, Kinect scans all pixels x in the depth map I, calculates the feature values $f_\theta(I,x)$ for each pixel using the formula, compares them with the threshold to determine the direction of descent (left branch or right branch), and proceeds step by step downward until the sample falls into a leaf node, thereby obtaining the probability $P_t(c \mid I,x)$ for the corresponding region c. Once all decision trees have been learned, the final classification result is determined according to a specific strategy, as shown in Equation (11), with the average value serving as the classification result:

$$P_t(c \mid I,x) = \frac{1}{T}\sum_{t=1}^{T} P_t\left(c \mid I,x\right) \tag{11}$$

3.2.3. Skeleton Generation Algorithm Based on Mean Shift

The results of human body part recognition are at the pixel level, with each pixel in the human body contour assigned to a specific body part region. However, these are merely simple pixel sets and cannot directly support real-time skeleton tracking. Therefore, skeleton generation is required to aggregate the three-dimensional position information of skeleton nodes, thereby obtaining complete human skeletal information. Kinect uses the MeanShift algorithm to aggregate pixels in body part regions into skeleton nodes, which is commonly used to quickly find peaks in high-dimensional data distributions and reduce the number of function calculation iterations. The algorithm is essentially a gradient optimization algorithm that can stably and effectively obtain the local maximum position of the density distribution function in a discrete data set obtained from the density function, and is widely used in professional fields such as machine vision.

Given a discrete data set collected by the density function, the corresponding probability distribution function is:

$$P(x) = \frac{1}{n}\sum_{i=1}^{n} K\left(x - x_i\right) \tag{12}$$

Use kernel functions:

$$K(x - x_i) = ck\left(\left\| \frac{x - x_i}{h} \right\|^2\right) \tag{13}$$

Approximate equation (13). Use the gradient descent method to solve:

$$\nabla P(x) = \frac{1}{n}\sum_{i=1} \nabla K\left(x - x_i\right) \tag{14}$$

The Mean Shift vector is represented as the vector between the center of the specified window and the centroid of the window. The goal of this algorithm is to converge the Mean Shift vector of the current window to 0 through multiple iterations, thereby approximating the position of the local maximum of the density of the discrete data window.

This skeleton aggregation method is performed at each node, using a weighted Gaussian kernel function to define the density distribution estimation function for each part of the human body as:

$$f_c(\hat{x}) \propto \sum_{i=1}^{N} w_i \exp\left(-\left\| \frac{\hat{x} - \hat{x}_i}{b_c} \right\|^2\right) \tag{15}$$

In this context, $\hat{x}$ denotes the three-dimensional coordinates of a pixel in the world coordinate system corresponding to the depth map, N is the total number of pixels in the human figure, b_c is the width of each body part after training, and w_i is the weight value of the pixel. $\hat{x}_i$ is the position of the pixel $\hat{x}$ after being mapped to three-dimensional space based on the corresponding depth $d_I(\hat{x}_i)$. Considering the part identification probability of the pixel and the surface information of the three-dimensional space, the definition of w_i is as follows:

$$w_i = P(c \mid I, x_i) \cdot d_I(x_i)^2 \tag{16}$$

3.3. Construction of a Dance Teaching Platform Based on Augmented Reality Technology

The use of augmented reality technology in digital sports dance education aims to create a networked, virtualized learning environment for sports dance, thereby reducing the time and space constraints associated with specialized sports dance training. From a hardware design perspective, the overall architecture of the digital sports dance education platform is shown in Figure 3. The platform consists of two main modules: the server and the client. Information is transmitted between these modules via communication interfaces. The server includes a web server and a database server, which support the functionality of the sports dance education platform. Among these: the database server supports the operation of the virtual component library, manages and maintains the file library, and provides file and data support technology. The client integrates various functions of the sports dance teaching platform, such as sports dance movement preview, simulation training, virtual interaction, experience summarization, and community discussion.

Application research is conducted in areas such as three-dimensional scene modeling, motion sensing information collection, construction of three-dimensional human movement models, and human motion posture recognition. The teaching server is integrated with the constructed visualization virtual models and human movement postures, enabling students to engage in self-directed sports dance learning and training even without teacher guidance.

This formula ensures that the user's distance from the camera does not affect the probability value, and the aggregation accuracy is improved to a certain extent. When Kinect performs real-time tracking of skeletal joints, it uses the human body part classification map obtained in the previous step as input and aggregates pixels using the above density estimation function to obtain the positions of human body joints.

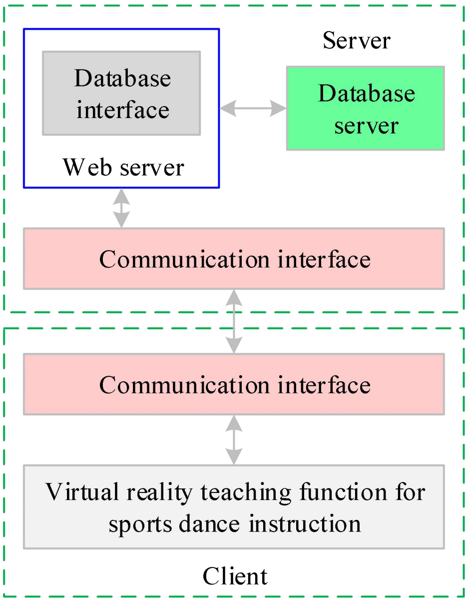


Figure 3. Architecture of Digital Sports Dance Teaching Platform.

3.4. Construction of a Three-Dimensional Model of Human Movement

During the performance of sports dance movements on the human body: First, depth data in a single direction is collected using the Kinect motion sensing device. The camera origin coordinate system is transformed into the world coordinate system to obtain an initial reconstruction model. Then, a dynamic sampling ray tracing algorithm is used to perform depth reconstruction on the three-dimensional model of human movement. Finally, texture mapping is applied to complete the realistic modeling of the three-dimensional human body model.

3.4.1. World Coordinate System Conversion

First, the collected depth data is converted from two-dimensional vertices into three-dimensional data. Floating-point data is used to replace the original depth frame data, and combined with camera coordinate data, the floating-point data is converted into point cloud data, which is consistent with the orientation of the Kinect camera. The specific method is as follows:

$$M_t(u) = B_t(u)K - 1[u,1] \tag{17}$$

$$M_t^c(u) = T_t M_t(u) \tag{18}$$

$$n_t^c(u) = U_t n_t(u) \tag{19}$$

In this context, K denotes the intrinsic calibration matrix of the Kinect motion capture device camera, u represents a known point in the image, whose depth value and normal vector are described by $B(u)$ and $n(u)$, respectively, while T_t and U_t represent the translation matrix and rotation matrix of the camera's pose transformation, respectively.

Next, estimate the pose information of human motion. By continuously collecting pose data during the camera's movement through a registration algorithm, and calculating the relative pose between the Kinect sensor device and the initial frame at each time step, the displacement and rotation transformation between adjacent frames can be obtained. In summary, this enables the transformation from the camera origin coordinate system to the world coordinate system.

3.4.2. Dynamic Sampling Ray Projection Algorithm

Traditional ray tracing algorithms can perform depth reconstruction on preliminary human body reconstruction results. The principle is as follows: starting from each pixel in the sample image, a ray is emitted along the viewpoint direction, and the ray passes through the 3D data field. Along each ray, a fixed number of equidistant sampling points are selected at a fixed sampling frequency. The opacity and color values of the sampling point are determined by performing cubic linear interpolation based on the opacity and color values of the eight nearest data points. The algorithm principle is illustrated in Figure 4.

In traditional algorithms, the sampling frequency of each ray passing through the 3D data field is consistent, and the sampling points are equidistant, resulting in a large computational load per unit time and slow image rendering speed. Based on human visual characteristics, hierarchical detail models can dynamically adjust the sampling frequency during rendering. When an object is closer to the viewpoint, a more detailed model representation is used, while a coarser model representation is used when the object is farther away, thereby improving rendering speed. The principle of the improved sampling frequency proposed in this paper is shown in Figure 5.

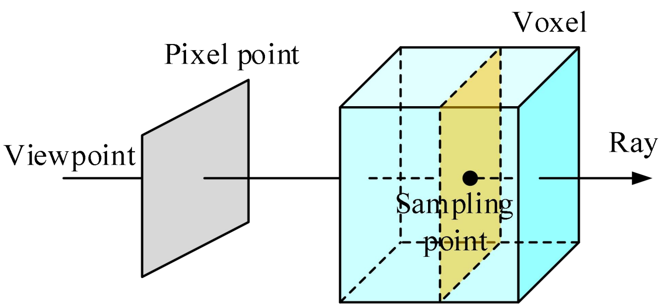


Figure 4. Traditional ray projection algorithm.

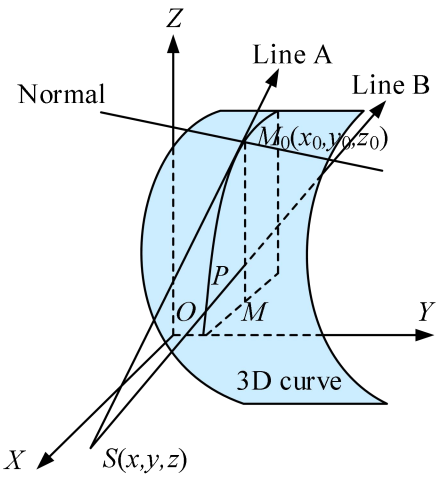


Figure 5. The principle of improving the sampling frequency.

Light projection and sampling frequency are related.

According to the algorithm principle shown in Figure 4, two rays A and B are emitted from the viewpoint S. Let ray A be tangent to the edge of the three-dimensional surface, and ray B pass through S to the closest point P on the three-dimensional surface. At the intersection point $M_0(x_0, y_0, z_0)$ of the surface and the section normal on ray A, the partial derivative $z = f'x(x_0, y_0)$ exists, which can be expressed as:

$$f'x\left(x_0, y_0\right) = \left.\frac{\partial f}{\partial x}\right|_{\substack{x=x_0 \\ y=y_0}} \tag{20}$$

Equation (20) represents the slope k_0 of the line of sight A relative to the X axis. Similarly, the tangent plane at point P is parallel to the Z axis and has the maximum slope k_0. When the surface is convex, the slope k_0 is positive, but when the surface is concave, the slope k_0 often becomes negative. Therefore, this paper defines the slope k_0 at the tangent point M_0 as:

$$k_0 = \left|f'x(x_0, y_0)\right| \leq 1 \tag{21}$$

The distance between viewpoint S and M_0 can be expressed as:

$$\left|SM_0\right| = \sqrt{(x_0 - x)^2 + (y_0 - y)^2 + (z_0 - z)^2} \tag{22}$$

Therefore, the sampling frequency $rate$ at point M_0 can be expressed as:

$$rate = \frac{k_0}{\left|SM_0\right|} = \frac{\left|f'x(x_0, y_0)\right|}{\sqrt{(x_0 - x)^2 + (y_0 - y)^2 + (z_0 - z)^2}} \tag{23}$$

In the dynamic sampling ray projection algorithm, the closer a part is to the observer's viewpoint, the greater the tangent slope, the smaller the distance from the viewpoint to the tangent point, the higher the sampling rate, the more pixels projected onto the screen, and the clearer the image. Conversely, the farther away from the observer's viewpoint, the smaller the slope of the tangent point, the greater the distance from the viewpoint to the tangent point, the lower the sampling rate, the fewer pixels projected onto the screen, and the more blurry the image. The sampling frequency dynamically adjusts its size according to changes in the observer's viewpoint, thereby effectively reducing computational load and improving image rendering speed.

3.4.3. Human Motion Pose Matching

Standard data on teachers performing sports dance movements was collected using motion capture technology. A multi-feature fusion algorithm was used to match the three-dimensional human movement model with sports dance movements, thereby completing the construction of an augmented reality dynamic movement system. Equations (24)-(26) were used to score movement recognition based on distance and angle features:

$$Q=\begin{cases} f(a_{\max})\left[(L_\beta-L)\dfrac{100-Q_\beta}{Q_\beta}+Q_\beta\right] & 0\le L\le L_\beta \\ 0 & L\ge L_\beta \end{cases} \tag{24}$$

$$f(a_{\max})=\begin{cases} 1-\dfrac{0.3}{H_2}a_{\max}^2 & 0\le a_{\max}\le\sqrt{\dfrac{10}{3}}H \\ 0 & a_{\max}>\sqrt{\dfrac{10}{3}}H \end{cases} \tag{25}$$

$$Q=Q_1\lambda_1+Q_2\lambda_2+Q_3\lambda_3 \tag{26}$$

Among these: L_β and Q_β represent the predefined standard angle difference threshold and the predefined baseline matching degree parameter, respectively. $f(a_{\max})$ denotes the penalty factor for pose matching accuracy. λ_1, λ_2, and λ_3 represent the feature weights for different movements in sports dance, respectively. determined based on the contribution of each action feature during the implementation of sports dance.

After obtaining the three-dimensional model of human movement and achieving human posture matching, based on sports dance teaching standards and practical needs, the teaching server is connected with the constructed visualization virtual model and human movement posture to build a real-time sports dance movement digital teaching platform based on augmented reality technology.

3.5. Analysis of Dance Posture Correlation Parameters

3.5.1. Dance Movement Estimation

This paper uses cosine similarity as the similarity function. By measuring the cosine value of the angle between the dot products of two vectors in the measurement space, the degree of difference between them can be quantified. Compared to Euclidean distance metrics, cosine similarity places greater emphasis on the directional differences between two vectors.

Cosine similarity not only measures the directional differences between vectors but also quantifies the similarity and differences between angles. Due to individual differences among humans, such as variations in height, weight, and arm length, but with consistent body proportions, angular similarity can also be used to measure whether limb movement amplitude aligns with standards. If the value approaches 1, it indicates that the dancer's movements align with standard movements, indicating proper dance technique; if the value approaches 0, it indicates significant deviation from standard movements.

Based on the cosine similarity calculation, the correlation parameters of the main movement postures at the arm are determined. The key movement correlation parameters of the subject are compared with the standard movements. Table 1 shows the correlation parameters of the standard movement posture for the left arm, and Table 2 shows the correlation parameters of the tested movement posture for the left arm.

The range of parameters related to the posture correlation between standard dance movements and test dance movements, the two sets of parameters $sim(V_2,V_{s\tan d})$, $corr(V_{LLarm},V_{LFarm})$, $corr(V_{LFarm},V_{s\tan d})$ are (-0.03, 0.02), (-0.02, 0.13), and (-0.004, 0.02), respectively, with mean differences of -0.00154, 0.01537, and 0.00372, respectively. This indicates that augmented reality technology has a good effect on the posture estimation of dance movements.

Table 1. The correlation parameter of the standard motion attitude of the left arm.

Timing sequence	$sim(V_2, V_{s\tan d})$	$corr(V_{LLarm}, V_{LFarm})$	$corr(V_{LFarm}, V_{s\tan d})$
0~1s	0.6425	0.9315	0.9536
1~2s	0.7042	0.9636	0.9968
2~3s	0.7269	0.9752	0.9642
3~4s	0.7152	0.9753	0.9569
4~5s	0.6826	0.9587	0.9852
5~6s	0.6425	0.9653	0.9578
6~7s	0.5636	0.9585	0.9636
7~8s	0.7215	0.9685	0.9752
8~9s	0.6856	0.9812	0.9436
9~10s	0.6578	0.9648	0.9752

Table 2. The correlation parameter of the motion attitude of the left arm.

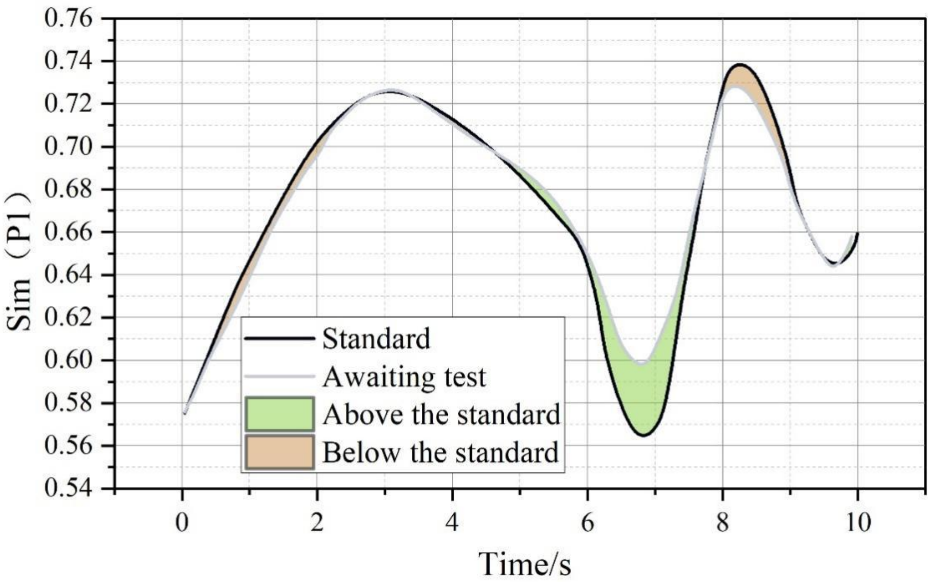
Timing sequence	$sim(V_2, V_{s\tan d})$	$corr(V_{LLarm}, V_{LFarm})$	$corr(V_{LFarm}, V_{s\tan d})$
0~1s	0.6345	0.9425	0.9536
1~2s	0.6935	0.9618	0.9848
2~3s	0.7215	0.9758	0.9648
3~4s	0.7155	0.9658	0.9536
4~5s	0.6934	0.8348	0.9885
5~6s	0.6531	0.9642	0.9536
6~7s	0.5934	0.9436	0.9648
7~8s	0.7158	0.9648	0.9686
8~9s	0.6835	0.9728	0.9348
9~10s	0.6536	0.9628	0.9678

Table 3 shows the relative error of the dance movements of the test subjects, estimating the degree of deviation of each test subject's dance movements from the standard movements. For the $sim(V_2, V_{s\tan d})$ indicator, the values for the time intervals 0–1 s, 5–6 s, 7–8 s, and 8–9 s are 1.3254, 1.4185, 0.8245, and 1.0398, respectively. These values are close to 1, indicating that the dance movements of the test subjects during these four time intervals align well with the standard dance movements, demonstrating proper dance technique. The average value is 1.14716, which is also close to 1, further confirming the proper execution of the dance movements.

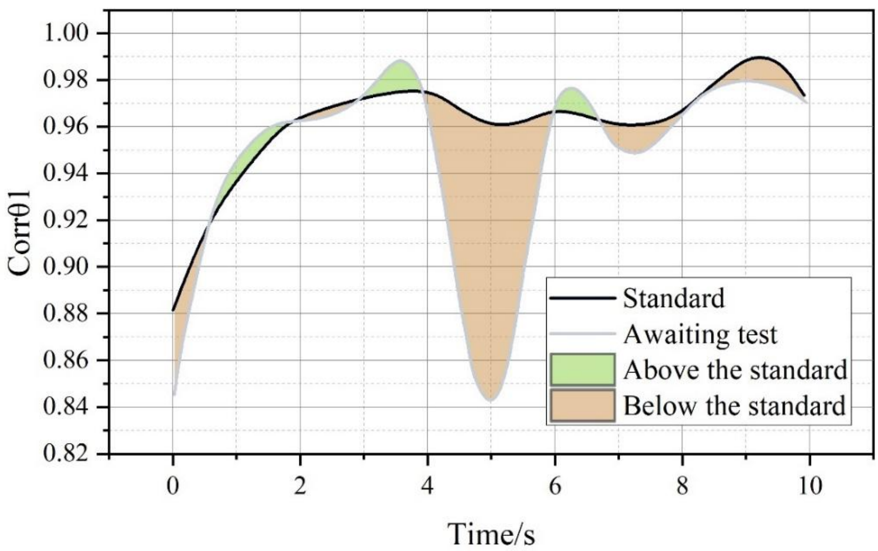
Table 3. The relative error of the motion of the object.

Time sequence	$sim(V_2, V_{s\tan d})$	$corr(V_{LLarm}, V_{LFarm})$	$corr(V_{LFarm}, V_{s\tan d})$
0~1s	**1.3254**	0.7288	0.1485
1~2s	0.6152	0.1069	0.7785
2~3s	0.0569	0.1255	0.1385
3~4s	0.2485	0.6364	0.1425
4~5s	0.1348	12.5642	0.0165
5~6s	**1.4185**	0.1128	0.0155
6~7s	5.6482	0.9566	0.1385
7~8s	**0.8245**	0.0152	0.9985
8~9s	**1.0398**	0.7968	0.1936
9~10s	0.1598	0.4048	0.5848

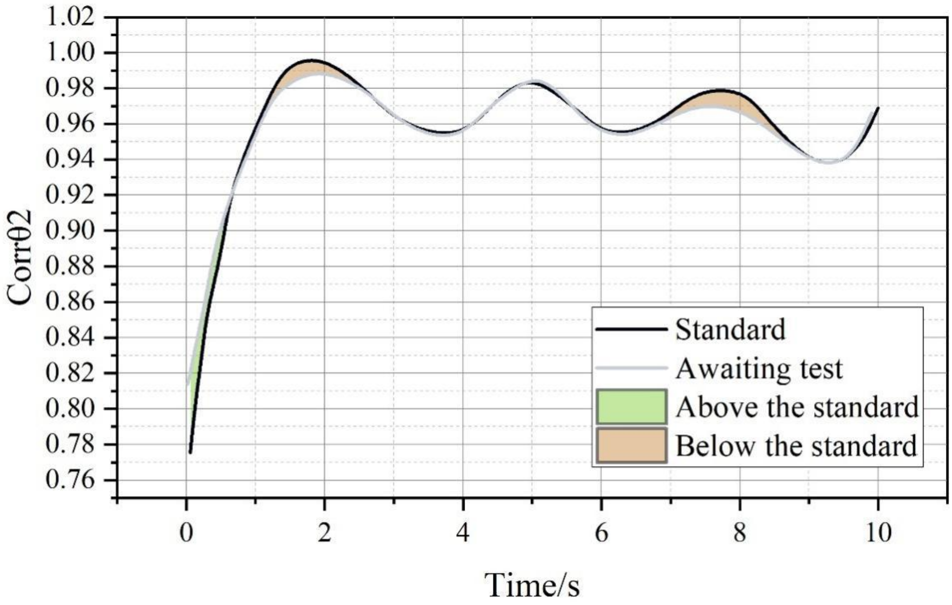
The experimental platform used in this study was a PC equipped with a Core i5-3470 3.2GHz CPU and 4GB of memory, with MATLAB serving as the development environment. The motion database created for this study contained 20 sets of dance movement segments, with each set comprising approximately 500 frames. The experimental subjects were randomly selected college students, all of whom had prior dance experience. First, the experimental subjects were required to imitate the standard movements of the dance instructor and perform corresponding dance movements under an optical motion capture system. The motion features of the left arm joint of the experimental subjects were extracted. Taking a real-time captured local motion sequence as an example, the differences between the main movement changes of the test subjects and the standard movements were analyzed. This paper primarily focuses on experimental comparisons of the final movements of the left arm within a single dance movement segment (0–10 seconds). In the experiment, an error threshold of $C \leq 2$ was set. Through feature pose difference comparison, parts that did not meet the threshold were screened out. The bending degree of the elbow during the 4–5-second time interval and the swinging amplitude of the left arm during the 6–7-second time interval of the test subjects showed significant differences from the standard movements. This paper uses the feature plane as the basic calculation plane to compute three discriminative parameters. Figure 6 shows the time series of left arm movement correlation parameters (0–10 seconds), with Figure (a) depicting differences in left arm movement direction, Figure (b) showing differences in left arm joint angle movement, and Figure (c) illustrating differences in the angle between the left arm and the torso. The differences between the tested movement and the standard movement are clearly evident in the figures. Among these, the differences in the direction of left arm movement and the angle between the left arm and the trunk are relatively small, with maximum difference values of 0.11729 and 0.056, respectively, between the standard dance movement and the tested dance movement. However, the difference in the movement of the left arm joint angle between the standard dance movement and the tested dance movement is relatively large, at 0.13551. Overall, the differences between the tested and standard parameters for left arm movement correlation do not exceed 0.15.



(a) The left arm movement direction is different



(b) The Angle of Angle movement of the left arm



(c) Angle difference between left arm and torso

Figure 6. The left arm movement correlation parameter sequence (0~10s).

3.5.2. Similarity Comparison

Using traditional three-dimensional model similarity comparison methods based on Euclidean distance to directly compare two sets of data, the results of posture analysis are often inaccurate for dance movements with large ranges of motion. For subjects with different heights, weights, and body proportions, the model itself may exhibit displacement errors. Figure 7 shows the x-axis distance differences for individual feature points. Without specifying the subject's movement position, this often leads to excessive spatial displacement errors. Figure 8 shows the Euclidean distance differences for individual feature points.

For the difference in distance between a single feature point and the x-axis, there are six feature points with relatively large differences, ranging from 5.67873 to 22.8733. The Euclidean distance difference of the feature points fluctuates between 0.20052 and 24.72426, with the maximum Euclidean distance difference of the feature points not exceeding 25.

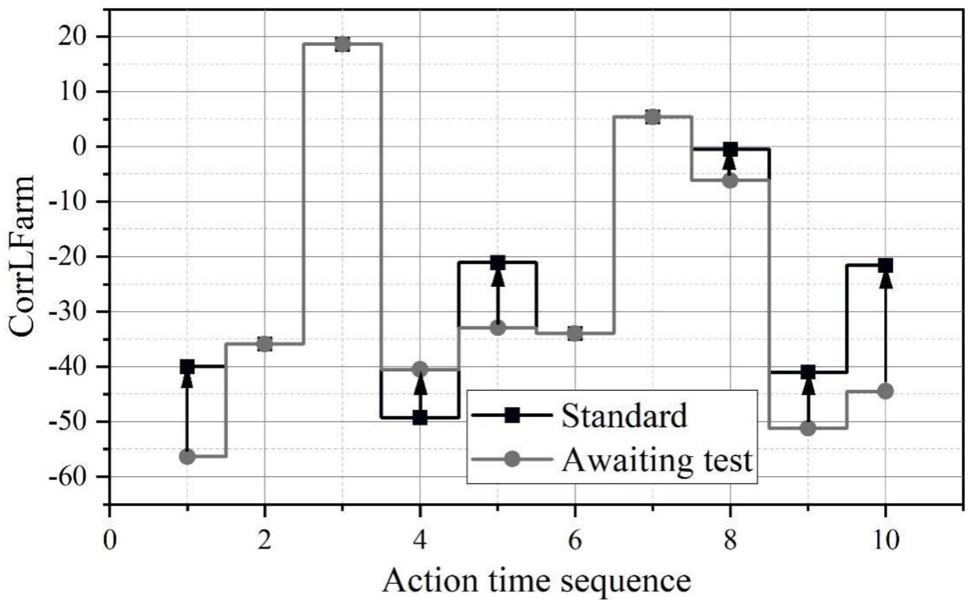


Figure 7. A single eigenpoint x distance deviation.

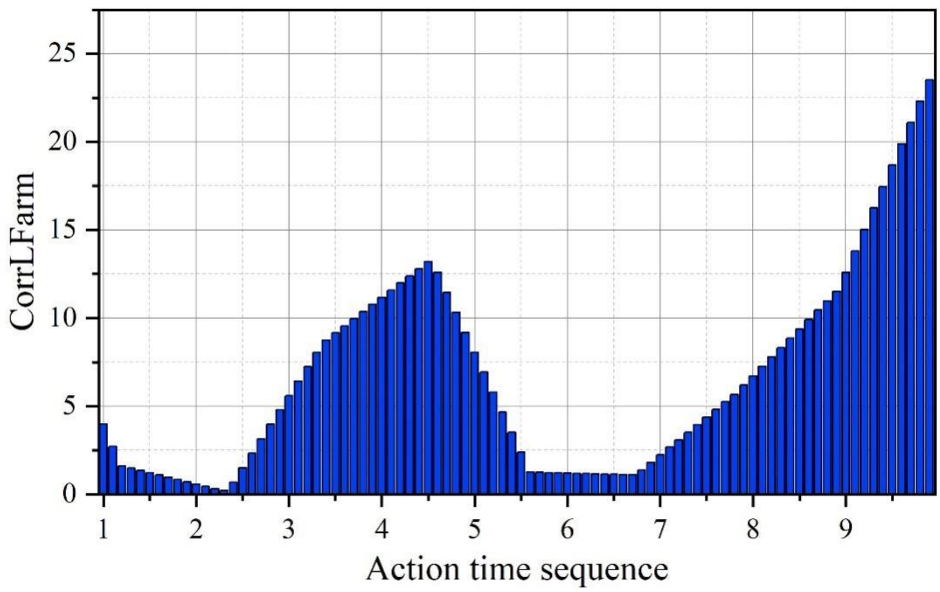


Figure 8. The difference between a single eigenpoint and a European distance.

Through experimental verification, the Kinect-based motion posture analysis method can clearly and efficiently detect differences and standardization between moving objects, demonstrating high robustness and providing scientific theoretical support for dance training.

4. Research on the Effects of Immersive Experiences in Dance Education

4.1. Research Subjects and Methods

This paper takes the immersive learning experience of college students in a specialized dance class in the sports major as its research subject.

4.2. Research Methods

4.2.1. Literature Review Method

Conduct research, collect, and organize materials related to the immersive learning experiences of college students majoring in sports dance from the "China National Knowledge Infrastructure Database" and "China Journal Net," as well as relevant literature related to this study, to provide a reference basis for this research project.

4.2.2. Questionnaire Survey Method

(1) Survey participants

Using cluster sampling, the survey participants were 50 students from the 2020 class and 45 students from the 2021 class of the sports dance elective class at Northwest Minzu University, for a total of 95 students, including 45 female students and 50 male students.

The 95 students were divided into an experimental group and a control group, with 47 students in the experimental group and 48 in the control group. Students in the experimental group learned through the dance teaching platform constructed in this paper, while those in the control group used traditional methods for dance learning.

(2) Distribution and Collection of Questionnaires

To fully support this study, a questionnaire was developed based on an immersive learning experience scale found in the CNKI database, which was subsequently revised and improved by other scholars. The questionnaire consisted of 20 closed-ended multiple-choice questions. Through dimensionality reduction factor analysis, two questions with low contribution rates were deleted, resulting in the immersive learning experience scale. The questionnaire was distributed and collected during the break in the sports dance class. A total of 95 questionnaires were distributed, and 95 were returned, with a 100% return rate and a 100% validity rate.

4.2.3. Mathematical Statistics Method

Data statistics were performed using SPSS Statistics 21.0 for data entry and analysis. Statistical methods appropriate for the research objectives were applied to the survey data, including descriptive statistics and independent samples t-tests.

4.3. Research on the Experience of Dance Education and Teaching Models Using Augmented Reality Technology

4.3.1. Dance Ability Score

Table 4 shows the independent samples t-test for dance ability scores and the post-test independent samples t-test for dance theory knowledge scores. The experimental group had an average score of 83.0486, while the control group had an average score of 71.7856. An independent samples t-test was conducted on the post-test data of the experimental group and the control group, with a P-value of 0.0015, which is less than 0.05, indicating a significant difference. This indicates that the teaching model proposed in this paper can significantly improve students' dance theory knowledge levels. It also suggests that the teaching model proposed in this paper is more effective than traditional teaching methods in helping students master dance theory knowledge.

In terms of technical skills, the experimental group had an average score of 34.2898, while the control group had an average score of 31.2968. When comparing the pre- and post-test data of the experimental and control groups using an independent samples t-test, the p-value was 0.0395, which is less than 0.05, indicating a significant difference. This indicates that the teaching model proposed in this paper is more effective than traditional teaching methods in enhancing students' creative abilities.

The experimental group scored an average of 4.3658 in thinking skills, while the control group scored 3.0846. An independent samples t-test was conducted on the post-test data of both groups, yielding a p-value of 0, which is less than 0.05, indicating a significant difference. This suggests that the teaching model proposed in this paper is more effective than traditional teaching methods in enhancing students' thinking skills.

Table 4. Test of independent sample t of dance ability.

Theoretical knowledge					
Project	Group	N	$(\bar{x} \pm s)$	T	P
Theoretical knowledge	Experimental group	47	83.0486±2.6485	-3.5948	0.0015
	Control group	48	71.7856±1.8694		
Technical skill					
Project	Group	N	$(\bar{x} \pm s)$	T	P
Technical skills	Experimental group	47	34.2898±0.6485	-2.2483	0.0395
	Control group	48	31.2968±1.2658		
Thinking level					
Project	Group	N	$(\bar{x} \pm s)$	T	P
After thinking level	Experimental group	47	4.3658±0.1958	-4.1254	0.0000
	Control group	48	3.0846±0.2642		

4.3.2. Satisfaction with Dance Learning

Figure 9 shows the satisfaction analysis of the dance education model under augmented reality technology. Satisfaction is divided into the following dimensions: course, teaching, platform, expectations, perception, and overall. The mean scores for each dimension are 4.3283, 4.4639, 4.0534, 4.4854, 4.4822, and 4.414, respectively, all of which are greater than 4 points. This indicates that the teaching model constructed in this study has been recognized by students, and the overall learning experience is satisfactory. The highest score was for expectation satisfaction, with an average of 4.4854, indicating that students clearly perceive their overall comprehensive abilities have improved significantly after completing this course. Next was perceived satisfaction, with a score of 4.4822, indicating that teachers maintain a good overall teaching state, and their teaching attitude, teaching quality, and teacher-student interaction are recognized by students. This course is generally accepted by students, and they have a strong willingness to continue learning under this teaching model.

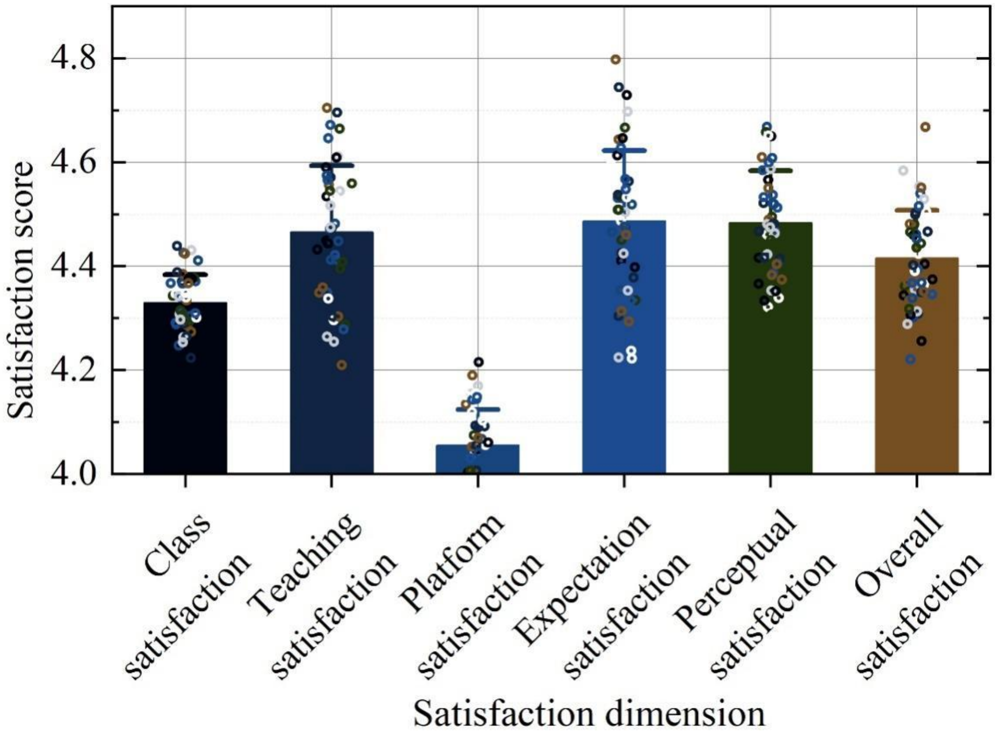


Figure 9. The satisfaction analysis of the dance education model in reality technology.

4.4. Analysis of the Application Effects of Immersive Virtual Learning Environments

A correlation analysis was conducted between the use of augmented reality technology and the effectiveness of immersive learning experiences, with the results shown in Figure 10.

The independent variables of immersive tendencies (learning difficulty, engagement, and focus) showed significant correlations with the dependent variables of immersive experience, presence, flow, and learning experience. No significant correlations were found between other independent and dependent variables in the data analysis. The immersive capability of the user interface exhibited significant correlations with the subscale of negative impact, tension/frustration, flow, and challenge in the learning experience. Through a specialized analysis of learning experience characteristic data, it was found that experimental participants with higher neuroticism had lower flow experiences (r = 0.6588, $p \geq 0.05$), as well as lower scores in the ability (r = 0.8769, $p < 0.01$), sensation, and imagination immersion dimensions of the learning experience scale (GEQ) (r = 0.6758, $p \geq 0.05$). Learners with high learning engagement exhibited a positive effect on the attention dimension of the Immersion Tendency Questionnaire (ITQ) (r = 0.7169, $p < 0.01$).

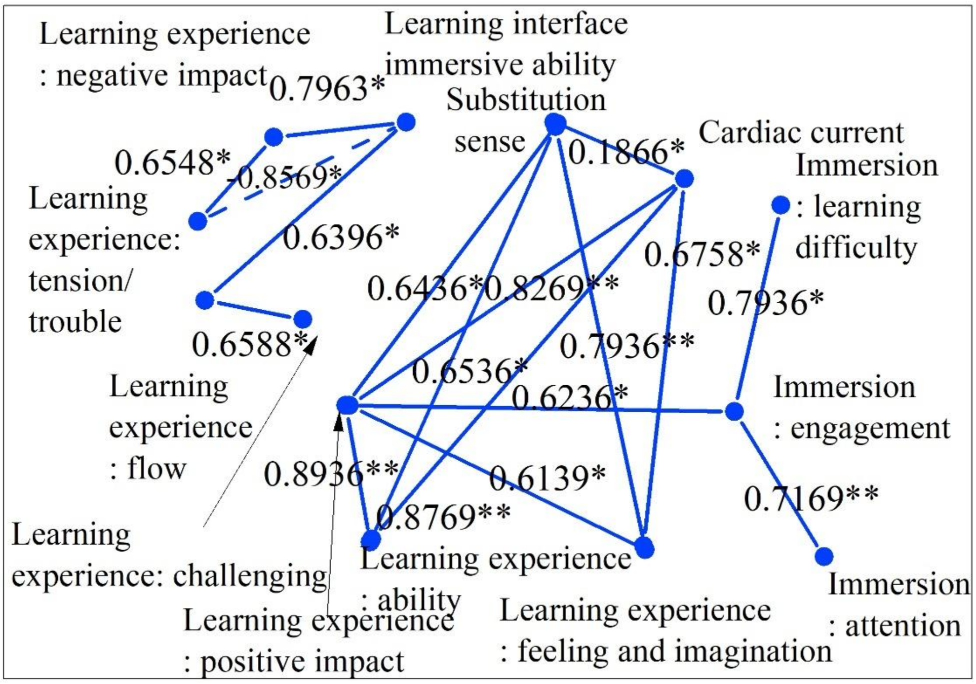


Figure 10. Characteristics of Learning Experience and Effects of Immersive Learning experience. (* $p <$ 0. 05,** $p < 0.01$, n = 47).

The research results also indicate that immersion and flow in the learner experience are related to learners' positive attitudes and abilities in immersive virtual learning environments, which means that immersion and flow have an impact on learners' task performance in immersive virtual learning environments.

5. Conclusion

This paper explores the application methods and mechanisms of augmented reality technology in dance education. Through digital image processing of dance movements and Kinect joint tracking algorithms, a human dance movement skeleton is generated. An augmented reality-based dance teaching platform is constructed. The cosine similarity function is used as the dance posture similarity estimation function to evaluate the effectiveness of the dance postures obtained by the model. The distance difference between individual feature points and the x-axis indicates that there are six feature points with significant differences, with a range of 5.67873 to 22.8733. Additionally, the Euclidean distance differences of feature point estimates fluctuate between 0.20052 and 24.72426, with the maximum Euclidean distance difference not exceeding 25. Kinect-based motion posture analysis can provide scientific theoretical support for dance training. A comparative analysis of the experience of dance education models under augmented reality technology was conducted. The experimental group scored an average of 83.0486, while the control group scored 71.7856. An independent samples t-test on the post-test data revealed a p-value of 0.0015, which is less than 0.05, indicating a significant difference. This suggests that the teaching model proposed in this paper is more effective than traditional teaching methods in helping students master dance theory knowledge.

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