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Innovative Education Model and Thinking Training Based on the Art of Dance

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SUMMARY: *The current research has created a computer-assisted three dimensional teaching system based on the skinning algorithms and EWMA algorithms to recognize dance movements and quantify GL-Compound similarity, and thus has developed a computer-based innovative dance education framework. The experimental group that employed the combined 3D system was compared with the control group that received traditional teaching using dance students in a university as subjects. The results show that the experimental group scored significantly higher in technical quality (p=0.001), musical interpretation (p=0.000) and choreography (p=0.002). In particular, the experimental group obtained a mean technical quality score of 86.37 (control group: 79.04), a mean musical interpretation score of 89.46 (control group: 81.22), and a mean choreography score of 88.52 (control group: 80.73). The model, which uses multimodal data capture and smart analysis, offers a great tool in improving specific dance technical skills and can be used as a viable tool in the process of modernization of dance education.*

KEYWORDS: *dance instruction; skinning algorithm; EWMA algorithm; dance similarity quantification; three-dimensional assistance system*

1 Introduction

With technological advancements, evolving market demands, and deepening cultural exchanges, dance education is undergoing a series of innovations and adjustments [1, 2]. These transformations reflect new understandings within the educational field regarding artistic practice and professional preparation, while also showcasing educators' reimagining of training models for future dance artists. Innovation serves as both a new engine for the times and a fresh driving force for socioeconomic development; cultivating innovative talent remains the enduring mission of higher education institutions [3]. Against the backdrop of realizing the great rejuvenation of the Chinese nation, exploring new models of innovative education in higher education institutions and integrating such education into talent cultivation processes holds significant social practical value and academic application value for effectively enhancing college students' innovative awareness, capabilities, and spirit [4, 5]. Fundamentally, innovative education cultivates students' ability to identify and solve problems. Problem identification requires a spirit of critical inquiry, while logical thinking serves as the prerequisite and foundation for this critical spirit [6, 7]. Without fundamental logical reasoning skills, students are prone to falling into the trap of blind faith or total rejection. Incorporating logical thinking training into innovation education not only prevents extreme judgments but also elevates the quality of their thinking. This allows their individual thinking to develop fully,

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thereby cultivating their innovative awareness and capabilities[8].

Innovative dance education has made significant strides in integrating technology and pedagogy. With the rapid advancement of intelligent technologies, educators increasingly adopt cutting-edge tools to enhance teaching quality and efficiency [9, 10]. Li, X conducted an in-depth analysis of literature on dance education innovation, comparing differences between China and other countries in campus dance education innovation. This innovative educational model has been shown to effectively stimulate active learning interest, thereby promoting the innovative development of dance pedagogy [11]. The integration of software coding in the education of dance was made by Zhang, Z et al. to bring about a creative digital dance design. The approach is more than the traditional challenge of directing student attention in dance education. By dance data innovation, technology inspired movement design, and code-based dance design, it enhances the creative problem solving thinking of students [12]. Zhang, J. identified the central importance of digital and AI technologies in the gathering and analyzing of instructional information. These technologies are used to maximize the learning habits of dance students, their behavior performance, and curricula design, which allows providing a personalized approach to the process of dance education [13]. Rahayu et al. were the first to create learning aids and online teaching media that were specifically designed to be used in dance education. Their effectiveness in dance instruction has been proven in simulation tests, and students have successfully completed distance dance training through the internet [14]. Zhu et al. investigated the impact of digital tools (learning platforms, virtual reality, and motion capture) on dance education. These tools make up the gaps in conventional dance education, improve the results of teaching and culture preservation, and encourage the growth of dance education in digital settings [15].

The extensive incorporation of technology and dance education is pushing educational patterns towards increased efficiency, accuracy and personalisation. Such technological uses help to streamline teaching procedures as well as provide learners with a wider variety of learning methods and career opportunities [16, 17]. Wang examined the existing use of virtual reality and augmented reality technologies in the context of dance education, and stated that dance education systems based on digitalization are effective in developing dance skills, improving the environment of teaching, and fostering creative development by combining both virtual and physical components in the process of teaching dance [18]. Li and M. have compared between virtual reality-based and conventional dance teaching models in terms of the dance techniques and choreography abilities of the students. Their findings suggest that the VR-based model has benefits, which include an increase in students dance abilities and classroom participation[19]. Li and M. have compared between virtual reality-based and conventional dance teaching models in terms of the dance techniques and choreography abilities of the students. Their findings suggest that the VR-based model has benefits, which include an increase in students dance abilities and classroom participation [20]. Zheng et al. incorporated Chinese language and culture in teaching dance art. This new way of teaching motivated students more and spread Chinese culture and dance art further. It was found that the effectiveness and interest in learning dance increased by over two times in the elementary school students, college students and adults [21]. Juxia investigated certain pathways of innovation in dance education under the paradigm of the Internet +. It was made possible to promote the improvement of students dance skills by providing a digital dance learning environment to excite the interests of students while maximizing the spread of specialized dance knowledge, which facilitated a boost in student motivation [22]. Zhou et al. created and implemented a data-based teaching model in the ethnic dance courses. This new method, which involved integrating the constructivist perspective of learning, multicultural education, and experiential learning, allowed the cultivation of the dance skills of the students. 78.58 percent of respondents reported positive feelings about the results of teaching, and the mean score of dance skills rose to 20.33 [23]. The author used digital technologies such as support vector machine models to identify human dance movements. Through this methodology, he came up with personalized teaching plans of students in university dance classes. The technique helped to make the dance movement of the students standardized and increased their dance awareness [24].

Online tools and data analytics are transforming the conventional dance training. With the implementation of digital video analysis software, new opportunities to learn and teach dance movements are available since teachers and learners can replay every movement immediately and carefully assess its technical execution accuracy and artistic representation [25]. At the same time, the use of data analytics as a personalized teaching tool is coming of age. Through the evaluation of students practice data, teachers can tailor personal teaching plans based on the pace of each learner [26, 27].

In this paper, skinning algorithms are firstly used to create smoothed human motion models that solve joint deformation discontinuity problems. With character/environment modelling and motion capture system support, it allows designing customized choreography. The efficiency of 3D motion rendering is improved by a new dynamic ray-sampling projection algorithm. Fusion pose matching algorithm based on multiple features and GL-Compound global-local parameter system yields accurate quantitative assessment of dance movements. A comparison with six popular human motion segmentation methods is made to determine the effectiveness of the suggested dance motion segmentation approach. The effect of frame rate on pose recognition accuracy is analyzed in terms of pose recognition accuracy as the measure of evaluation. The feature-based pose dissimilarity is used to conclude the analysis of dance poses. Controlled experiments are planned to confirm the applicability of this computer-assisted dance art innovation model.

2 Development of a Computer-Based 3D Assisted Dance Instruction System

In the context of the digital revolution in art education today, the dance as a holistic art form needs to be innovative in terms of its creative and educational models to liberate itself of the constraints of the conventional approach of relying on experience. Conventional dance instruction, which relies on the demonstration by teachers and imitation by pupils, can impart stylistic rhythms, but encounters serious obstacles regarding the analysis of movement accuracy, offering individualised feedback as well as facilitating cross-temporal and space-based creative cooperation. The choreographer, in creating dances, is also limited in terms of his total design of movement shapes, spatial layouts and character-environment interaction, due to the lack of intuitiveness of two-dimensional drawings or rehearsals on location, which makes it hard to provide dynamic visual previews and scientific assessments. This paper will discuss innovative educational programs in the field of dance art with the goal of improving dance education based on experience to data-driven models by introducing the use of computerized three-dimensional systems.

2.1 Dance Movement Recognition

2.1.1 Action Model

Choreographers need to analyze dance movements and poses in detail when designing them, considering various angles of view. Most often, the human head and limbs are depicted as three-dimensional objects. Skinning algorithms are mainly used by the system to create motion models. By using this method, linear interpolation calculations are performed based on skin vertex data and skeleton weights to compute skin vertex positions on every new frame, which allows decomposing and calculating human movement. The formula is the following:

$$v' = \sum_{i=1}^{n} w_i M_i D_i^{-1} v \quad \sum_{i=1}^{n} w_i = 1 \tag{1}$$

In this formula, the vertex coordinates of the human skin before and after deformation are denoted by v and v', respectively. At the initial state of the motion model, the coordinates corresponding to the skin vertex in the local coordinate system of the i th bone segment, along with the transformation matrix obtained after transforming from the local coordinate system to the global coordinate system, are denoted by $D_i^{-1}v$ and M_i, respectively. The weight corresponding to the i th bone segment and the current skin vertex is denoted by w_i. The system employs a skinning algorithm to construct the dance motion model, enabling smooth deformation of dance movements and preventing joint discontinuities in the human body.

2.1.2 Character and Environment Models

The computer-aided 3D dance creation system offers choreographers expanded options, most notably in dance movement models and environmental models. Establishing character imagery requires consideration of height, age, and distinctive traits. Once fundamental requirements are met, choreographers can further refine character attire, 3D models, skin textures, hairstyles, and subtle movements. All character models are stored in MAX format, with elements ranging from character height to intricate movements and clothing materials designed using 3DS MAX. Character motion design is achieved through motion capture systems. For motion detection, the system employs the EWMA algorithm. This algorithm first calculates the skeletal vector angles frame-by-frame from human skeletal nodes captured by sensors. It then sets appropriate weighting parameters α and calculates the control factor α_i for each frame data in exponential increments based on temporal sequence. The calculation formula is as follows:

$$\alpha_i = \alpha(1-\alpha)^i \tag{2}$$

Finally, the system will perform a weighted calculation on the current smoothed value X based on the data values within the recorded time period, after completing the calculation according to the above formula. The calculation formula is as follows:

$$\hat{X} = \sum_{i=1}^{n} (\alpha_i X_i / \sum_{i=1}^{n} \alpha_i) \tag{3}$$

Choreographers can use this system to either select elements from the library or create their own. After uploading movements to the server, they undergo comparison and analysis before being incorporated into the database. This enables staff to update the entire system in real time, ensuring the vividness and expressiveness of dance movements. 3DS MAX software also facilitates stage lighting, curtain, and smoke simulations. Within the post-production dance sound effects model library, staff can not only upload independently created music assets but also utilize the computer-aided 3D dance creation system for necessary searches.

2.1.3 Three-Dimensional Human Movement Model

Traditional ray tracing algorithms can perform depth reconstruction on preliminary human body reconstruction results. The principle is as follows: Starting from each pixel point on the sample image, a ray is emitted along the viewpoint direction, traversing the three-dimensional data field. Along each ray, a fixed number of equidistant sampling points are selected at a predetermined sampling frequency. The opacity and color values of the sampling point are then determined by performing cubic linear interpolation based on the opacity and color values of the eight nearest data points. The algorithmic principle is illustrated in Figure 1.

In traditional algorithms, the sampling frequency for each ray passing through the 3D data field is uniform, and sampling points are equidistant. This results in high computational load per unit time and slow image rendering. Based on human visual characteristics, hierarchical detail models can dynamically adjust sampling frequency during rendering. When objects are closer to the viewpoint, a finer model representation is used; conversely, a coarser model representation is employed to improve rendering speed. The principle of the improved sampling frequency proposed in this paper is illustrated in Figure 2.

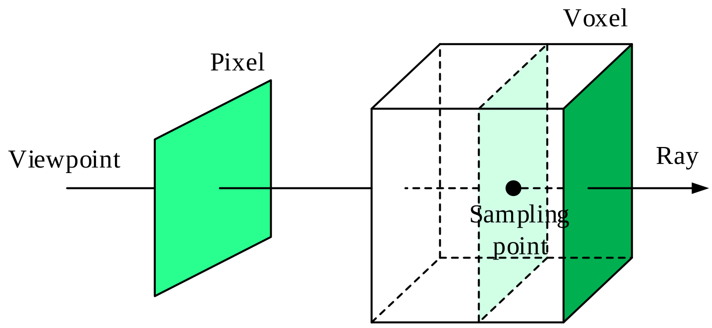


Figure 1: Traditional Light Projection Algorithm

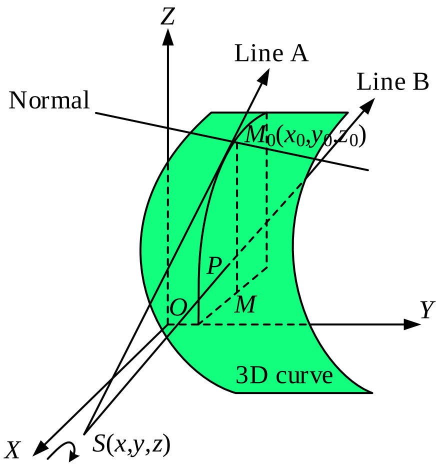


Figure 2: The Principle of Improving Sampling Frequency

According to the algorithmic principle shown in Figure 2, two rays A and B are emitted from viewpoint S. Let ray A be tangent to the edge of the 3D surface, and ray B pass through S to the closest point P on the 3D surface. At the intersection point $M_0(x_0, y_0, z_0)$ of the surface normal and the section normal along ray A, the partial derivative $z = f'(x)(x_0, y_0)$ exists and can be expressed as

$$f'_x(x_0, y_0) = \left.\frac{\partial f}{\partial x}\right|_{\substack{x=x_0 \\ y=y_0}} \tag{4}$$

Equation (4) represents the slope k_0 of the line of sight A relative to the X -axis. Similarly, it can be seen that the tangent plane at point P is parallel to the Z -axis and has the maximum value of slope k_0. When the surface is convex, the slope k_0 is positive. However, 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

$$k_0 = |f'_x(x_0, y_0)| \leq 1 \tag{5}$$

The distance from viewpoint S to M_0 can be expressed as

$$|SM_0| = \sqrt{(x_0 - x)^2 + (y_0 - y)^2 + (z_0 - z)^2} \tag{6}$$

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

$$rate = \frac{k_0}{|SM_0|} = \frac{|f'_x(x_0, y_0)|}{\sqrt{(x_0 - x)^2 + (y_0 - y)^2 + (z_0 - z)^2}} \tag{7}$$

When using adaptive ray-tracing algorithms, tangent gradients are commonly larger at regions closer to the position of the observer. Sampling density increases as the distance between the viewpoint and the tangent location reduces, hence more pixels are projected on the screen and the displayed picture becomes sharper. In contrast, areas further away from the observer tend to have lower tangent gradients. The increase in the distance between the viewpoint and the tangent location results in the decrease of sampling density and hence fewer pixels are projected on the screen and a less clear image is obtained. Adaptive changes in sampling density are made based on variations in the position of the viewer, thus, decreasing the computational load and enhancing the rendering performance.

2.1.4 Human Pose Matching

Standard data of teachers' dance movements were collected using motion capture technology. A multi-feature fusion algorithm was employed to match the 3D human motion model with dance actions, thereby constructing a virtual reality dynamic motion system. Equations (8) to (10) were utilized to evaluate action recognition scores based on distance and angle features.

$$Q = \begin{cases} f(a_{\max})\left[\left(L_\beta - L\right)\dfrac{100 - Q_\beta}{Q_\beta} + Q_\beta\right] & 0 \leq L \leq L_\beta, \\ 0 & L \geq L_\beta; \end{cases} \tag{8}$$

$$f(a_{\max}) = \begin{cases} 1 - \dfrac{0.3}{H^2} a_{\max^2} & 0 \le a_{\max} \le \sqrt{\dfrac{10}{3}} H, \\ 0 & a_{\max} > \sqrt{\dfrac{10}{3}} H, \end{cases} \tag{9}$$

$$Q = Q_1\lambda_1 + Q_2\lambda_2 + Q_3\lambda_3 \tag{10}$$

where: L_β and Q_β denote the predefined standard angular difference threshold and the predefined baseline matching degree parameter, respectively; $f(a_{\max})$ represents the penalty factor for pose matching accuracy; λ_1, λ_2, and λ_3 denote the feature weights for different dance movements, determined based on the contribution of each movement's characteristics during dance execution.

2.2 Quantitative Evaluation of Dance Movement Similarity

2.2.1 Data Standardization

Dance data captured using Vicon motion capture equipment was processed and exported into a motion analysis .htr file. This file contains spatiotemporal data for the 53 captured joint markers. This data will serve as the template motion data for the dance teaching system and will be used in the learning assessment module for comparison with dance learning data. Since student motion data is captured using monocular pose estimation technology, the motion capture tabular data requires standardization before comparing the two sets of action data. This involves retaining specific joint markers corresponding to the 24 key joints in the pose estimation. The mapping of these 24 joints to corresponding markers is detailed in Table 1.

Table 1: The corresponding joint nodes of the 24 joints

Posture estimation joint	Vicon Motion Capture	Posture estimation joint	Vicon Motion Capture
Right shoulder	RSHO	Left shoulder	LSHO
Right elbow	RELB	Left elbow	LELB
Right knee	RKNE	Left knee	LKNE
Right ankle	RANK	Left ankle	LANK
Right foot	RTOE	Left foot	LTOE
Right wrist	RWRA	Left wrist	LWRA
Right middle finger	RMFIN	Left middle finger	LMFIN
Right thumb	RTFIN	Left thumb	LTFIN
Right hip	RASI	Left hip	LAST
Abdomen and waist region	STRN	Neck	CLAV
Right ear,right eye	RFHD,RBHD	Left ear,left eye	LRHD,LBHD

2.2.2 Dance G-L Motion Parameters

In past digital dance instruction, when comparing user movements to template actions, the process first constructs a set of three-dimensional spatial position points for each joint. During computation, two methods are commonly employed: the first involves simply calculating the Euclidean distance between the teacher's and student's joint point sets; the second focuses on the two joint vectors formed between three key points, solving for the cosine angle between these vectors to achieve similarity comparison. The computational processes for both methods are illustrated in Figure 3, with the left and right panels depicting Euclidean distance and cosine angle calculations, respectively.

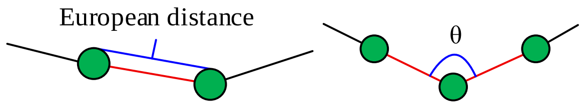


Figure 3: The solution process of the two methods

However, simple point set Euclidean distances and joint angles can only capture local features of movements, failing to adequately account for the complexity of human motion in dance instruction. There remains a lack of unified constraints on global features, making it difficult to accurately assess users' learning proficiency and movement accuracy. Therefore, it is necessary to reference dance tutorials and expert opinions to develop more suitable feature representations for dance movements.

The GL-Compound body activity region segmentation is illustrated in Figure 4. After thoroughly considering the complexity and technical demands of dance movements, this paper divides the 24 human joint points captured by pose estimation into regions as shown in Figure 4. These regions represent five core trunk areas—left hand (LH), right hand (RH), left leg (LL), right leg (RL), and upper body (UB)—along with one central root region encompassing the waist and abdomen. Since human joint movements can originate independently or indirectly follow parent joints, dance involves not only significant joint changes but also intricate hand gestures. In order to master dance, one must have knowledge about how the movement of the joint takes place along with its association with the movement of the proximal joints. Thus, there is a need for a hierarchical breakdown of the central areas of the body's trunk into the global and local levels. In this research paper, we have introduced the method of GL-Compound using the ideas of Global Motion Parameters (GMP) and Local Motion Parameters (LMP).

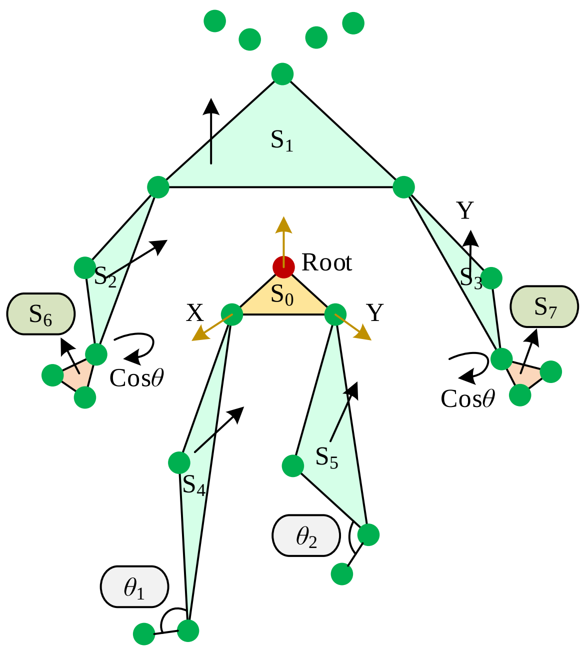


Figure 4: Division of Physical Activity Areas in GL-Compound

Define the five dark blue regions formed by the joints connected to the torso (shoulders, hips) and their child nodes as global planes. The light blue regions represent local planes describing palm movements, while the green region centered on the Root joint serves as the human body's central plane. The relative positional relationship between a global plane and the center plane reflects the approximate movement of the body region containing that global plane. The positional relationship between a local plane and its parent global plane reveals the local movement at the limb's extremity. The hierarchical representation of dance movement characteristics is shown in Table 2. By hierarchically dividing body parts into 1 central plane, 5 global planes, 2 local planes, and 2 local angles, the spatial position of each dance movement can be represented through the superposition of these 8 planes and the 2 ankle joint angles, from the global to the local level. The following section calculates movement parameters for the five core trunk regions (left hand LH, right hand RH, left leg LL, right leg RL, upper body UB) based on the aforementioned activity hierarchy types.

Table 2: Hierarchical Representation of Dance Movement Characteristics

Vertex	Adjacent points	Quantity	Activity level type	Naming
Articular joint	Left hip and right hip	1 unit	Central plane	S_0
Neck	Left shoulder and right shoulder	1 unit	Global plane	S_1
Elbow joint	Shoulder joint and wrist joint	One on each side	Global plane	S_2,S_3
Knee joint	Hip joint and ankle joint	One on each side	Global plane	S_4,S_5
Wrist joint	Middle finger and index finger	One on each side	Local plane	S_6,S_7
Ankle joint	Knee joint and sole of the foot	One on each side	Local perspective	θ_1,θ_2

The calculation method for the motion parameters of the left and right arms is identical. Taking the right hand (RH) as an example, its motion can be viewed as the superposition of two components: one is the global motion of the plane S_2 (comprising the upper arm and forearm) relative to the body center plane S_0; the other is the local motion of the palm S_6. In this example, a Cartesian coordinate system is established with the root joint as the spatial origin. The global Euclidean distances of the shoulder joint, elbow joint, wrist joint, and root joint in three-dimensional space are calculated on the global plane. Simultaneously, the angle between the normal vector of this global plane S_2 and the normal vector of the center plane S_0 is determined to obtain the GMP parameters for the right arm (RH). For the local parameters LMP, the local Euclidean distances between the middle finger, thumb, and their parent joint (wrist joint) are calculated. Simultaneously, the angle between the normal vector of the local plane S_6 and the normal vector of the parent global plane S_2 is determined.

$$d(p_1,p_2)=\sqrt{(x_2-x_1)^2+(y_2-y_1)^2+(z_2-z_1)^2} \tag{11}$$

Formula (11) calculates the Euclidean distance between joint nodes in three-dimensional space, where p_1 and p_2 represent the three-dimensional coordinates of the two joint nodes.

Any plane is formed by three key nodes. Assuming the coordinates of these nodes are $p_1(x_1,y_1,z_1)$, $p_2(x_2,y_2,z_2)$, and $p_3(x_3,y_3,z_3)$, the normal vector of this plane can be obtained by calculating the cross product of two vectors drawn from the same point:

$$\vec{V_1} = \overrightarrow{p_1 p_2} = (x_2 - x_1, y_2 - y_1, z_2 - z_1) \tag{12}$$

2.2.3 Dance Movement Similarity Calculation

After analyzing changes in dance poses, the GL-Compound method was adopted, utilizing global parameters combined with local parameters to represent the movement of different body regions. This section will define a pose similarity calculation method between learners and professional dancers based on the requirements of dance instruction.

Scoring feedback constitutes a vital component of dance instruction systems. During the learning process, as users replicate movements performed by the virtual instructor, the system captures the learner's body movements at predetermined beats. It then calculates the learner's motion parameters while simultaneously determining the action parameters of the standard movement primal corresponding to that beat. These two sets of data are subsequently compared to generate a similarity score.

Each beat of movement comprises five body trunk motion parameters and one core region parameter. The GMP parameter has a maximum data dimension of 4, while the LMP parameter has a maximum dimension of 3. Data for body parts not requiring consideration can be replaced with zeros, thereby establishing a 7-dimensional motion parameter set for each beat. Different fundamental movements correspond to distinct beat structures. Assuming the dance sequence being learned has n beats, the dataset for this sequence comprises n samples, each represented as a 7-dimensional vector. This organizes each fundamental movement group into an $n \times 7$ matrix. Dance scoring prioritizes the learner's overall coordination and movement proportions over minute joint-to-joint length variations. In light of this, cosine similarity is used to measure the degree of similarity between vectors for the actions and parameters for the body parts in question for each action set in one beat. In the testing phase, to make sure that the movements of the learner match those of the template while accounting for the difference in timing, an interface for the metronome is created. The interface gives both audio and textual instructions on the specific movements, and the participant must execute these movements within a specified timeframe.

$$s_i = \cos\theta = \frac{\vec{a} \cdot \vec{b}}{|\vec{a}| \times |\vec{b}|} \tag{13}$$

Formula (13) illustrates that when learners imitate movements, the feature vector $\vec{a}$ represents the movement parameters of a specific body part. In the standard primal movement, the feature vector $\vec{b}$ for that body part's movement parameters is defined. The closer the cosine similarity s_i approaches 1, the more similar the spatial movement states of the corresponding body parts become. Since different dance performance styles vary in the difficulty and emphasis placed on movements of different body parts, it is necessary to consider the importance and evaluation priority of each body part in dance. This involves assigning distinct weighting factors M_i to the similarity scores of each pair of body part feature parameters. The resulting similarity scores are then weighted, summed, and averaged using n as the denominator to determine the overall similarity score for the current complete, coherent movement sequence, as shown in Equation (14).

$$s = \frac{1}{n}\sum_{i=1}^{n} M_i s_i \tag{14}$$

When the overall similarity score $S < 0.5$, the learner's performance is considered subpar. When the overall similarity score is $S > 0.5$, the learner's movements are deemed standard. When the overall similarity score is $S > 0.8$, the performance is rated as highly proficient and excellent. Users are notified of body parts with lower similarity scores and advised to focus their practice on these areas.

3 Analysis of the Effectiveness of Computer-Assisted Dance Art Innovation Models

3.1 Computer-Assisted Dance Analysis System Usage Process

For the verification of the proposed technique, the experimentation phase makes use of an artificial data set that includes several dance movement sequences, each of which includes around 500 frames. In this case, the experimenters included 250 randomly selected college students who had previously performed dance actions. Initially, the experimenters directed the subjects to imitate the standard dance actions presented by a professional dance instructor through motion capture technology.

3.1.1 Dance Movement Segmentation

Using upper limb element movements as an example for action segmentation, the same principles apply to lower limb elements and continuous limb movements. The upper limbs generally do not bear body weight, so upper limb movements typically do not cause the body's center of gravity to shift. In dance movement analysis, for upper limb actions that do not bear body weight, the focus is on analyzing the final posture rather than the movement process. Given the flexible and varied movement patterns of the upper limbs and the emphasis on analyzing terminal postures, this paper employs a combined method of velocity thresholds and region segmentation to divide upper limb element movements. In most cases, when an upper limb movement begins, limb velocity gradually increases from slow to fast. As the movement nears completion, limb velocity gradually decreases. Consider arm swinging as an example: assume the arm first swings left, then right, comprising two distinct actions. As the leftward swing nears completion and the rightward swing is about to commence, the arm experiences a pause accompanied by a local minimum velocity. This scenario can be addressed using a velocity-based segmentation method, where the upper limb motion is divided at the point where the pause occurs. The segmentation points for the two arm-swinging actions mentioned above correspond to the local minimum points of the arm's velocity. In other words, whenever the limb's movement velocity drops below a certain threshold, it signifies the imminent start of a new action. Figure 5 illustrates the segmentation results based on the velocity threshold for a specific action in the dataset. The horizontal axis represents motion capture frame numbers, while the vertical axis shows limb angular velocity magnified by 100. Regarding threshold selection, considering significant limb length variations among individuals of different heights, this study employs angular velocity instead of linear velocity at the limb extremity. The set angular velocity threshold is approximately 0.18 radians per second.

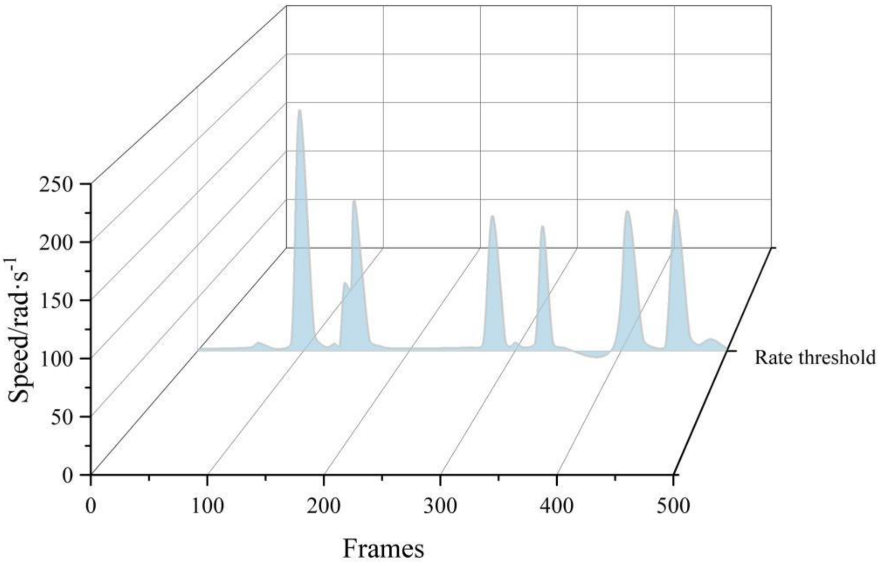


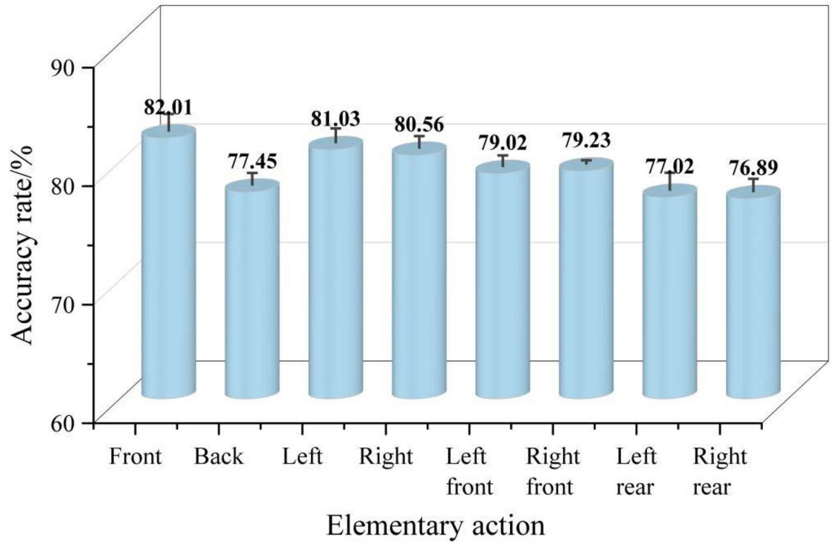
Figure 5: The segmentation result of the action rate threshold for a certain student

First, on the dataset, we compare our motion segmentation method with six other mainstream clustering-based human motion segmentation approaches. The reference clustering methods include: Sparse Subspace Clustering (SSC), Low-Rank Representation (LRR), Least Squares Regression (LSR), Ordered Subspace Clustering (OSC), Temporal Subspace Clustering (TSC), and Probabilistic Temporal Subspace Clustering (PM). The dataset comprises dance recordings from 250 university students. Five dance datasets (No. 2, No. 55, No. 91, No. 138, and No. 157) were randomly selected, each containing 4 to 18 actions. Table 3 shows the accuracy comparison between the six action segmentation methods and the proposed method. It can be observed that the proposed method achieved the highest accuracy across all datasets, with an average accuracy of 86.3%.

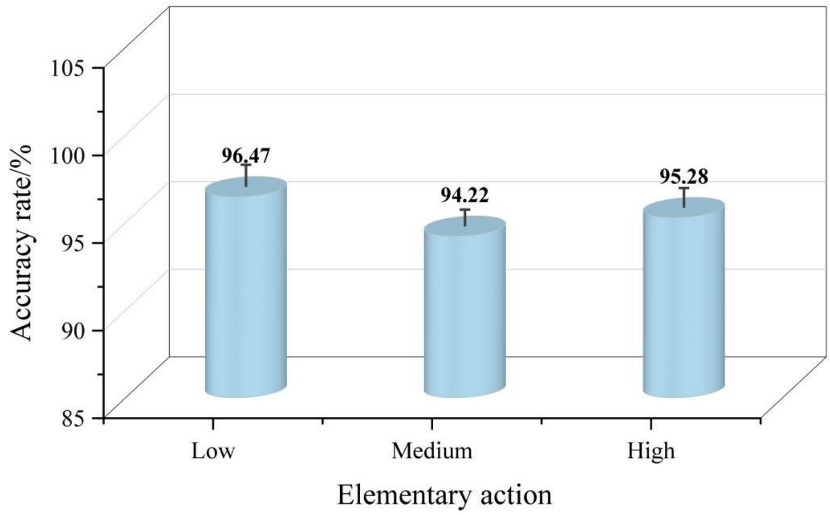
Table 3: Comparison Results of Accuracy Rates(%)

Algorithm	Five sets of motion capture data				
	Data No.2	Data No.55	Data No.91	Data No.138	Data No.157
SSC	60.28	68.37	71.26	62.44	70.53
LRR	62.46	66.12	60.48	63.27	68.36
LSR	69.38	69.16	65.24	68.93	67.62
OSC	70.22	68.83	69.47	67.31	70.28
TSC	76.36	84.44	83.17	85.68	79.33
PM	80.37	83.21	85.36	82.15	80.24
The proposed	80.48	85.36	90.12	88.35	87.19

In order to examine the effectiveness of the suggested segmentation approach on actions performed in various directions, this paper statistically evaluated the accuracy of segmentations in various directions, as illustrated in Figures 6(a) and 6(b). The figure quantifies separately the accuracy of 8 categories of horizontal-direction actions and 3 categories of vertical-direction actions. It has been observed that the average segmentation accuracy of horizontal actions is lower (79.15%) compared to that of vertical actions (95.32%). This difference does not only arise due to the larger number of horizontal categories, which makes it difficult to distinguish, but also because of other factors like the degree of limb flexion and rotation, as well as the randomness of direction movements, which contribute to the outcome of segmentation. Actions in horizontal plane in directions that are easy to correct and discern by the human eye, including but not limited to, front, left, and right, generally provide clear and distinct data of motion in most cases, hence the high segmentation accuracy. Although left front and right front can be visually corrected, deviations in these directions tend to be greater than in front, left, and right in different individuals. Therefore, the clarity of the motion data is somewhat reduced, which reduces the accuracy of segments. Of the three directions, namely back, left back, and right back, movement without visual correction tends to lead to hesitation. Such movements are less distinct and have relatively larger deviations, allowing confusion between adjacent areas to occur more easily. Therefore, segmentation accuracy is relatively low in the horizontal directions. With fewer categories, vertical directions are easier to distinguish and are characterized by greater tolerance to errors. Hence, overall segmentation accuracy is much higher when compared to horizontal directions.



(a)Horizontal direction



(b)Vertical direction

Figure 6: Results of accuracy rates for different directions of segmentation

3.1.2 Dance Movement Recognition

The model parameters are optimized by projecting the positions of 3D skeletal landmarks onto 2D landmark estimates in each frame. The weighted fusion is subsequently used to derive the 3D positions of human skeletal landmarks. Lastly, it is possible to determine the category of the action pose compared to what is considered standard actions.

Using pose recognition accuracy as the evaluation metric, with “Turning Over” and “Cloud Step” as test subjects, the impact of frame rate on pose recognition accuracy is measured. Specific accuracy results are shown in Figure 7. As the video frame rate increases, the recognition accuracy for both dance poses improves. At 120 frames per second, pose recognition accuracy stabilizes, with both “turning over” and “cloud step” achieving recognition rates exceeding 88%.

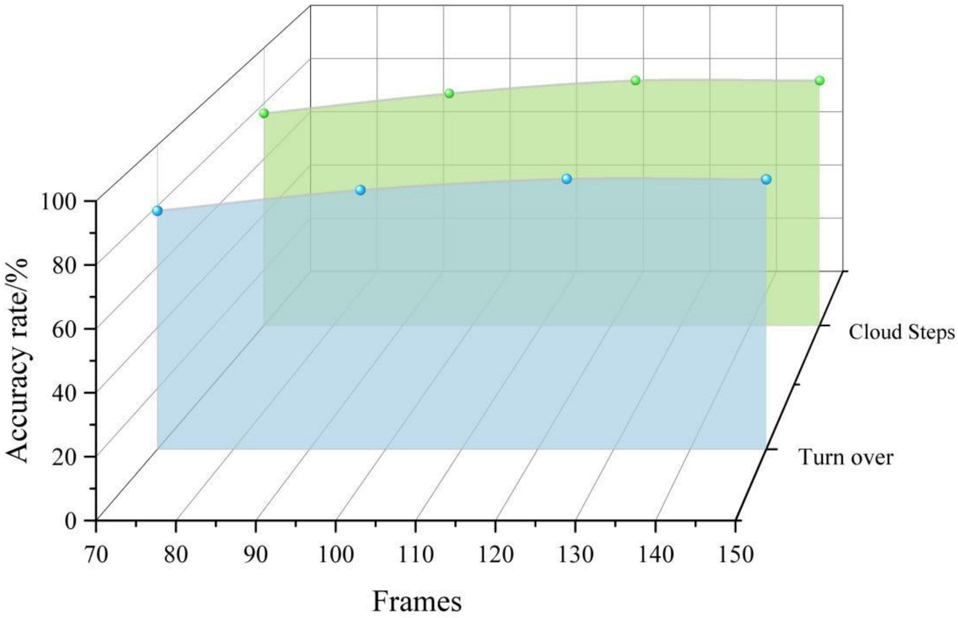
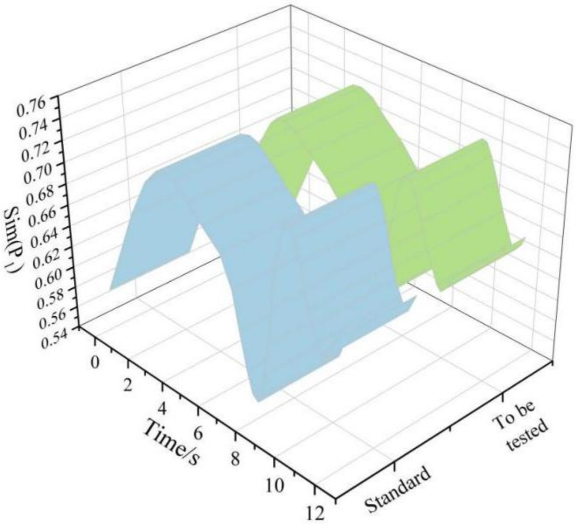


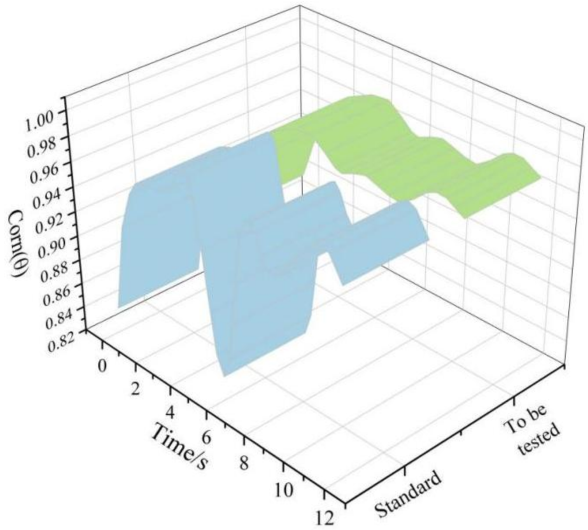
Figure 7: The impact of frame count on the accuracy of posture recognition results

3.1.3 Analysis of Dance Postures

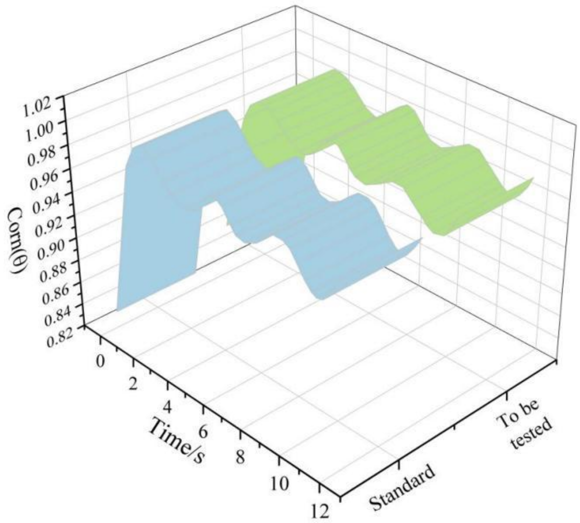
Experiments were conducted using data point 91 from the dataset, primarily comparing the final left arm position within single dance movements (0–12 seconds). An error threshold of $C \leq 2$ was set, and through feature pose difference comparisons, instances failing to meet this threshold were filtered out. Using the feature plane as the primary computational plane, three discriminative parameters were calculated. The comparative analysis of left arm movement postures is illustrated in Figures 8(a–c). The figures clearly reveal discrepancies between the test action and the standard action. For data point 91, the elbow flexion angle during the 5–7 second interval and the left arm swing amplitude during the 7–9 second interval both exhibit significant deviations from the standard action.



(a)Direction of movement



(b)Joint angle movement



(c)The angle with the trunk

Figure 8: Comparison of differences in left arm movement postures

The comparison based on the conventional three-dimensional model similarity measure which relies on Euclidean distance is performed on the basis of a direct comparison between two sets of data. Individual differences in the distances along the x-axis of the feature points are shown in Fig. 9. From the analysis, we learn that when the amplitude of the dancing actions is large, the pose estimation outcome often shows a low level of accuracy. This is due to intrinsic bias related to displacement in the model because of differences in height and weight of the subjects.

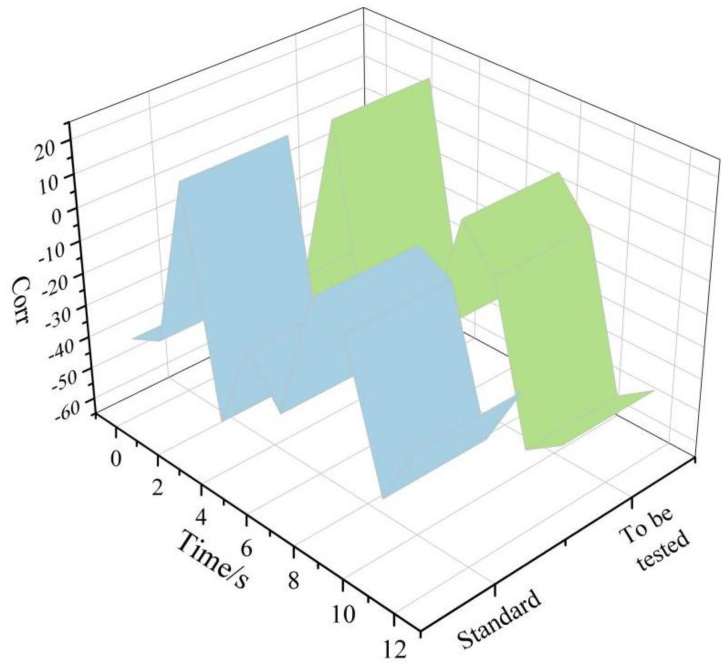


Figure 9: Difference in x-axis distance of a single feature point

3.2 Application Effect Analysis

To comprehensively evaluate the effectiveness of a dance innovation education model based on computer-aided 3D systems in practical teaching, this study designed a controlled experiment to investigate its actual impact on enhancing students' specialized dance technical skills. The study chose students of two parallel dance classes of a university using a quasi-experimental design. In one class, the experimental group (n=25) was taught via a training model that combined computerized 3D assistance systems with new educational thought. This involved the use of 3D motion capture, virtual reality dynamic feedback, multimodal motion analysis, and customized instructions. The second class was used as the control group (n=25) and followed the conventional dance teaching model, which focuses on instructor demonstration, pupil replication, oral correction, and repeat performance. Pre-experiment independent samples t-tests indicated that there were no significant differences in the two groups regarding dance fundamentals, specialized skills, and the period of learning ($p>0.05$) hence meeting the homogeneity requirements of the experiment.

The experimental period lasted 16 weeks and included three major modules, such as technical skills, musical expressiveness and choreography. After experiment, the two groups were extensively evaluated in three areas, namely, technical quality, musical interpretation and choreography. Assessments of technical quality, which involved the accuracy of the movements, stability, control of force, and coordination of the body were done through blind assessment by two dance instructors with more than ten years of teaching experience employing standardized scoring rubrics. The musical interpretation dimension tested the understanding of rhythm of students, the correlation between the emotion of music and dance moves, and the physical reaction to changing rhythms. The evaluation of choreography was based on creative expression in a specific theme, structure logic, as well as the smoothness and creativity in the combination of movements. Every score was registered in the range of 100 points. The inter-rater reliability, which was assessed using Cronbach’s alpha coefficient, was above 0.85 in all dimensions, which means that the internal consistency is very high.

The post-experiment comparison of specialized technical scores between the experimental and control groups is shown in Figure 10. The technical quality score means were 86.37 and 79.04, respectively. Homogeneity of variance was established with an independent samples t-test, which gave a significance level of P-value less than 0.001. This statistically significant finding shows that there is a considerable difference in technical quality between the two groups. The scores of musical interpretation in the experimental and control groups were 89.46 and 81.22. After an independent sample t-test and verification of the equal variance assumption, the significance result obtained a P-value of 0.000. Therefore, the statistical findings are important as they show that there is a significant musical interpretation discrepancy between the experimental and control group. The mean scores on dance choreography in the experimental and control groups were 88.52 and 80.73, respectively. After an independent samples t-test and verifying the assumption of equal variance, the significance result produced a p-value of 0.002. Therefore, the statistical findings were significant and it indicated that there was a significant difference in dance choreography between the experimental and control groups.

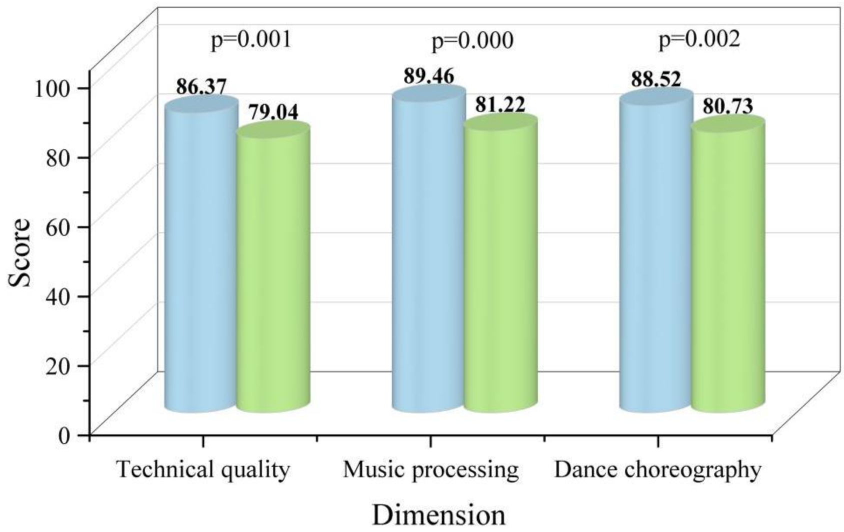


Figure 10: Comparison Results of Specialized Technical Scores

In summary, the dance innovation education model based on computer-aided 3D systems effectively enhances students' specialized technical proficiency, musical interpretation skills, and choreographic capabilities through multimodal data acquisition, intelligent analysis, and immersive feedback mechanisms. This validates the model's practical value and application potential in dance arts education.

4 Conclusion

The paper will explore the application value and practical pathways of computer-aided 3D systems in dance instruction in a systematic way, which will include both technological innovation and empirical research.

The suggested approach demonstrated the best segmentation accuracy over six popular motion segmentation techniques, and the averaged accuracy was 86.3 percent. Pose recognition was also consistent at 120 frames per second, where the rate of recognition of both turn and cloud step were above 88 percent. The procedure is both effective and efficient in identifying differences and standardization between moving objects and has a high level of robustness.

The findings of teaching experiments show that the experimental group was significantly superior to the control group in terms of technical quality (p=0.001) and musical interpretation (p=0.000), as well as choreography (p=0.002). In particular, the mean technical quality score was 86.37 (control group: 79.04), the mean musical interpretation score was 89.46 (control group: 81.22), and the mean choreography score was 88.52 (control group: 80.73).

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