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PAPER

The Impact of Mobile Applications on Personalized Learning Paths in Dance Education

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ABSTRACT

With the rapid development of smart mobile applications, mobile devices have become an essential learning tool in dance education. Traditional dance teaching methods often fail to effectively meet the individualized learning needs of students, especially in the dynamic learning and feedback of skills. As a result, the design and implementation of personalized learning paths have become a key issue in current dance education. Although existing research has preliminarily explored dance teaching on mobile platforms, problems still exist, such as inaccurate student dance posture assessments and incomplete personalized learning path recommendation mechanisms. Therefore, utilizing mobile application technologies to achieve precise dance posture recognition and evaluation, while providing personalized learning paths for each student, is a critical issue that needs to be addressed. This paper aims to explore the role of mobile applications in optimizing personalized learning paths in dance education. The study consists of two main parts: first, a dance posture evaluation method based on intelligent posture recognition technology is proposed to accurately match personalized learning content based on students' progress and skill levels. Second, a personalized learning path recommendation system based on collaborative filtering algorithms is designed to help students receive tailored content during their dance learning process. The study demonstrates that combining posture evaluation with content recommendation can significantly improve the personalization and learning outcomes of dance education, providing new technological support and practical applications for intelligent dance teaching.

KEYWORDS

mobile applications, dance education, personalized learning, posture recognition, collaborative filtering, learning path recommendation

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1 INTRODUCTION

With the rapid development of mobile Internet and smart technologies, mobile applications have become deeply integrated into people's daily lives and have become an important tool for various learning and educational activities [1–4]. In the field of dance education, traditional classroom teaching models often fail to meet the personalized needs of each student, especially in the learning of dance skills, where there are significant differences between students. How to design and assess teaching in a targeted manner has become a major challenge faced by educators [5–8]. The emergence of mobile applications provides a new opportunity for dance education. Through intelligent means, students can autonomously learn dance on mobile platforms and receive real-time feedback, making the design and implementation of personalized learning paths possible.

Personalized learning has become an important research direction in the field of education in recent years. Its goal is to provide customized educational content and learning paths based on each student's learning characteristics and needs [9–15]. As a subject that highly relies on physical skills and artistic perception, personalized learning is particularly important in dance. Through mobile application technologies, students can learn dance at any time and in any place and receive appropriate dance training and assessment according to their own learning progress and abilities [16–20]. Therefore, researching how to effectively support personalized learning in dance education through mobile applications not only has theoretical significance but also holds important value for innovation in practical dance teaching and learning models.

Although there are some studies on dance education and personalized learning, existing research methods still have some limitations. First, traditional dance teaching assessments mostly rely on the subjective judgment of teachers, lacking precise quantitative analysis of students' dance postures [21, 22]. Second, existing personalized learning path recommendation systems are mostly focused on the learning of basic knowledge, and for subjects like dance, which require dynamic feedback and skill adjustment, study on personalized recommendation strategies is still relatively weak. Finally, existing dance learning platforms focus more on content provision, lacking in-depth exploration and optimization of students' individual learning needs. Therefore, how to achieve precise assessment and personalized path optimization based on intelligent technologies remains a significant challenge in current study.

This paper aims to explore the impact of mobile applications on personalized learning paths in dance education, proposing two main research directions. First, the paper designs a dance posture evaluation method based on intelligent technology to adapt the learning content and pace to different students. Second, the paper proposes a recommendation algorithm based on collaborative filtering of learning content, aiming to optimize students' learning paths and help them more efficiently master dance skills. Through these studies, this paper not only provides new intelligent solutions for dance education but also offers new ideas and methods for the design of personalized learning paths.

2 DANCE POSTURE RECOGNITION AND EVALUATION FOR PERSONALIZED LEARNING CONTENT ADAPTATION

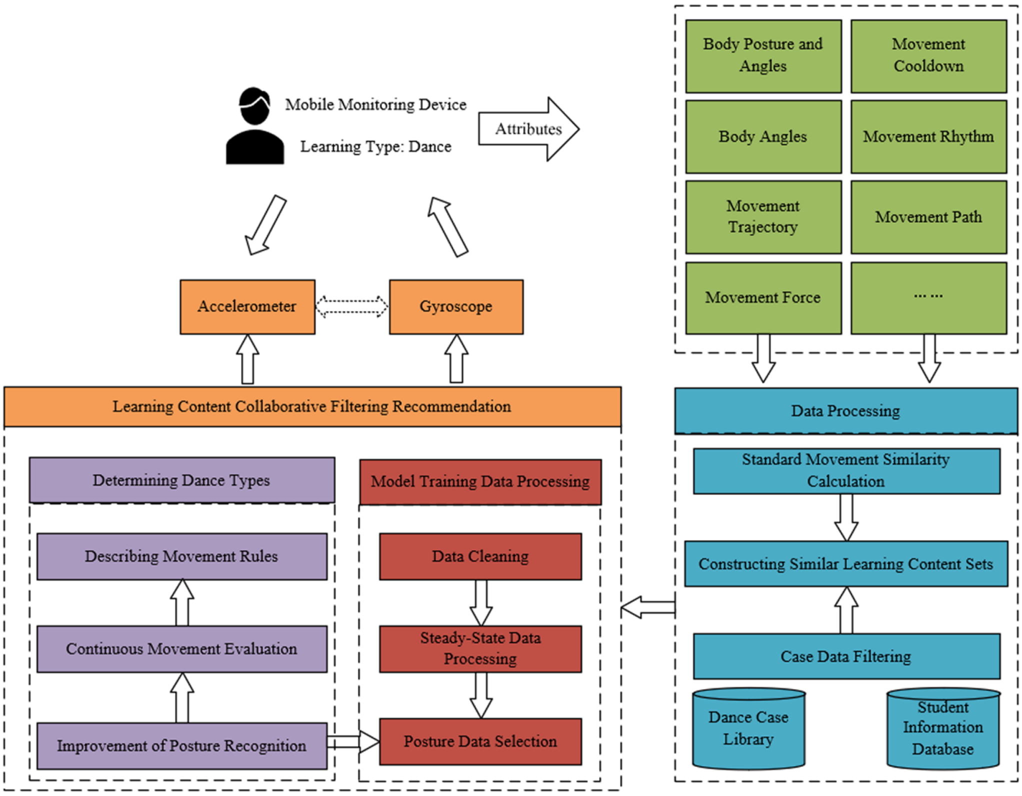

Fig. 1. Schematic diagram of student dance posture recognition and learning path recommendation process

The research approach of this paper is based on the combination of mobile device sensor data and intelligent recommendation algorithms, aiming to provide innovative solutions for personalized learning paths in dance education. First, this paper designs a student dance posture recognition and scoring module. By analyzing the motion data of students during dance practice, it can dynamically assess the coordination, rhythm, and technical performance of their movements. The built-in accelerometer and gyroscope of mobile devices can accurately capture the changes in students' body movements during practice. With the help of sensor data, the scoring module can dynamically evaluate the students' movements. For example, when a student shows high coordination and rhythm in a certain dance move, the scoring module will output the corresponding score, which serves as the basis for further learning path recommendations. Based on the students' posture recognition score results, this paper designs a personalized learning content recommendation mechanism combining collaborative filtering algorithms. Specifically, the recommendation system uses nearest neighbor selection and predicted scoring methods to analyze students' learning progress, preferred movement types, and learning behaviors, generating personalized course recommendations. For certain students, if they demonstrate strong coordination and rhythm in a specific dance style, the collaborative filtering algorithm will recommend more challenging advanced courses based on the learning trajectories of other students with similar performance. If a student shows good ability in rotation-type movements, content-based recommendation algorithms will further suggest dance courses that include more rotation techniques. Figure 1 illustrates the process of student dance posture recognition and learning path recommendation.

2.1 Dance movement scoring module introduction

Dance movement recognition is not just about tracking the key points of the body but also about extracting the key features of the movement during complex motions. These movement features are often multidimensional, including joint angle changes, limb motion trajectories, and overall posture fluidity. Due to differences in students' height, body type, and movement amplitude, directly extracting dance movement features from raw video data is often difficult to achieve accurately. Therefore, in order for the machine to effectively recognize and understand each student's dance movements, a set of clear rules must be used to standardize and unify the description of these movements. This approach not only reduces errors caused by individual differences but also helps the machine build more accurate movement models, thus improving the accuracy of dance movement recognition.

This paper chooses to use the detailed comparison method to determine students' coordination and rhythm during dance practice in a specific style. The detailed comparison method can accurately capture the key details of the human body during motion, such as joint angle changes, movement amplitude, and speed changes. These details are the core elements for evaluating dance movement coordination and rhythm. For example, in dance, coordination is often reflected in the synchronization and fluidity of body parts, while rhythm is embodied in the alignment of movements with the music beats. The detailed comparison method can precisely calculate the rate of change in joint angles and the amplitude of movement by real-time capturing of the student's body motion data, thereby evaluating the accuracy and coherence of the movements. This method is more detailed than simply relying on macro features and can more effectively identify subtle differences in students' practice, enabling more accurate evaluation of their coordination and rhythm.

By using the built-in accelerometer and gyroscope of the mobile device, the system can real-time capture the movement data of each student's joint, precisely recording the angle change, speed, and movement amplitude of each joint. These data reflect the changes in the student's body posture during dance and can be compared with standard dance movements using precise angle measurements. The standard dance movements have been modeled in the system using preset "standard joint angles," where each dance movement is represented by a combination of multiple joint angles. For example, assuming a standard dance movement has ten key joint angles, these angles can be treated as a point in a high-dimensional feature space. By comparing the student's current dance posture with these standard angles, we can use the Euclidean distance formula to calculate the deviation of each joint angle, thereby quantifying the gap between the student and the standard movement. Specifically, this paper calculates the Euclidean distance between the joint angles of the student's actual dance movements and the standard dance movement's angles to evaluate the accuracy of their coordination and rhythm. Suppose the joint angles of the standard movement are [StandAngle1, StandAngle2, …, StandAngle10], while the student's current joint angles are [Angle1, Angle2, …, Angle10]. By calculating the Euclidean distance between these two vectors, a quantified standard value can be obtained. The smaller this value, the closer the student's dance movements are to the standard, indicating better performance in coordination and rhythm. If there is a large deviation in a certain joint angle of the student's movement, this will directly affect the overall performance score. Since the coordination of various joints in a dance movement is closely related, the detailed comparison method can accurately identify problems in the movement details, such as excessive bending of a joint or failure to return to position in time. These issues will be promptly fed back to the student to help them and correct them.

Assuming the angle of each joint in the tested student's dance posture is represented by *xu*, and the standard angle values of each joint are represented by *tu*, the deviation from the standard movement is represented by $f(a,b)$, the Euclidean distance-based calculation formula is:

$$f(a,b) = \left(\sum\nolimits_{u=1}^{v} (xu - tu)^2\right)^{1/2} \tag{1}$$

In some dance styles that require the coordination of body and arm movements, the amplitude and rhythm of arm swings are important indicators of coordination and rhythm. To accurately assess students' movement coordination, the system analyzes the frequency of arm swings to determine if it aligns with the body movement amplitude. Specifically, when students perform accelerating movements, the arm swing frequency should adapt to the body's motion changes, meaning that as the speed increases, the arm swing frequency should first rise and then gradually decrease. By comparing the actual arm swing frequency of the student with the frequency model of the standard movement, the system can evaluate the student's performance in terms of coordination and rhythm.

When implementing this detailed comparison method, the arm swing is treated as a periodic change process. Suppose in a certain dance movement, the initial state of the arm swing is T1 (the stationary state), and at acceleration, the arm reaches the maximum swing amplitude at state T2. Afterward, the arm will swing back and forth between T1 and T2, forming a cycle. By real-time sensing the data from sensors, the system can calculate the time required for each arm swing to complete one cycle and derive the swing frequency for each cycle. The core of the detailed comparison method is to compare the student's actual arm swing cycle with the standard movement cycle and calculate the difference between the two. If the student's swing frequency significantly differs from the standard frequency, it indicates inaccurate rhythm or coordination problems. Furthermore, due to physiological differences such as arm length, direct comparison using angles alone is not suitable. Therefore, this study quantifies the accuracy of the student's arm swing frequency by using the average cycle time, ensuring fairness and personalization in the assessment. Suppose the student's average arm swing frequency in the dance is represented by $AV\,d(x)$. The specific calculation formula is as follows, with each $d(a)$ substituted for calculation:

$$d(a) = \frac{T_{a+1} - T_a}{\Delta S} \tag{2}$$

$$AV\,d(v) = \frac{\sum\nolimits_{1}^{v} d(a)}{v} \tag{3}$$

Assuming the average arm swing frequency in the standard movement is represented by *SAV d*(*y*), the similarity of the arm swing frequency is calculated using the formula below. The smaller the similarity *Q*, the closer it is to the standard movement, and vice versa.

$$Q = \left| AV\, d(x) - SAV\, d(y) \right| \tag{4}$$

For dynamic dance movements, especially those involving beats and durations, traditional static comparison methods may lead to misjudgment. For example, when the time difference between the student's movement and the standard dance movement is large, such as when a student takes one and a half or two beats to complete a movement while the standard dance movement requires one beat, the static comparison method cannot effectively assess whether the student's movement meets the standard. To address this issue, this paper proposes a dynamic posture calculation method based on joint angle change rates. This method monitors the rate of change of joint angles in real-time during the dance process, calculates the dynamic changes of each joint, and compares them with the change rates of the standard dance movement to obtain a new similarity measure.

Specifically, the dynamic posture calculation uses the rate of change of each joint angle as the core indicator of similarity between the standard dance movement and the student's actual movement. By using the accelerometer and gyroscope, the system can sense the movement state of each joint in real-time and calculate the rate of change of the joint angles. Suppose that in the standard dance movement, the rate of change of a certain joint angle within one beat is *A*, and in the student's actual practice, the joint angle changes to *B*. By calculating the Euclidean distance between the two, the system can quantify the dynamic difference between the student's movement and the standard dance movement. If the student's joint angle change rate is close to the standard movement, it indicates that the student's rhythm and coordination are close to the standard. On the contrary, if the difference is large, it may indicate coordination or rhythm deviation. Let the Euclidean distance of joint angle change rates be represented by *F*, and the time difference is Δs, which reflects the time difference between the joint angle from $t(u-1)$ to tu in the standard dance movement and the joint angle from $x(u-1)$ to xu in the measured dance posture. The calculation formula is:

$$F = \left(\sum_{u=1}^{v} \left(\frac{xu - tu}{\Delta s} \right)^2 \right)^{\frac{1}{2}} \tag{5}$$

Considering both the arm swing frequency and the joint angle change rate, the formula for calculating the dance movement similarity is:

$$DI = \partial F + (1 - \partial)Q \tag{6}$$

Because of differences in student height, the swing amplitude will also differ accordingly. This study chooses to reduce the weight of *Q*. Suppose the student's height in the standard dance movement is represented by G_t, and the height of the measured student is represented by G_x, the calculation formula for ∂ is:

$$\partial = -\frac{1}{\tau} \arctan \left| G_t - G_x \right| + 0.5 \tag{7}$$

When the student's height is the same, both F and Q need to be considered. When there is a large height difference between students, the weight of F becomes greater. Therefore, the final measure of similarity between the dance movement and the standard dance movement is DI. The smaller the DI, the more similar the movements, and vice versa.

2.2 Evaluation of students' dance movements

To achieve effective evaluation of continuous dance movements, a minimum similarity threshold needs to be set to determine whether a student's dance movements conform to the standard. This threshold is based on the analysis of the dynamic changes in the dance movements, specifically by calculating the similarity between the student's actual dance movements and the standard dance movements. The system uses built-in accelerometers and gyroscopes to sense in real-time the student's body movements and posture changes during dance practice. These sensors capture information such as the angle changes, speed, and movement amplitude of each joint, which are then used to define the corresponding "standard movement indicators" for each dance move. To assess the similarity between the student's dance movement and the standard movement, the system first calculates the range of joint angles for each standard dance movement and sets a reasonable similarity threshold based on this data. This threshold is typically defined based on the maximum difference in the standard movement dataset, ensuring that the system can tolerate a certain degree of error, especially considering the personalized differences and dynamic changes in the dance movements themselves.

In the specific implementation, the system prepares V standard dance movements in advance, recording the joint angles, speed, amplitude, and other relevant indicators of these standard movements in the database as benchmark data. Next, when the student inputs J training dance movements, the system calculates the similarity between each training movement and the standard dance movements one by one. For the convenience of calculation, the system first selects a key joint angle as the research target and then retrieves the minimum and maximum values of that joint angle from the database, which are set as the lower bound F and upper bound I, respectively. Then, in the training movements to be detected, the system calculates the actual value A of the joint angle and compares it with the corresponding indicators of the standard dance movements. The similarity is calculated using the Euclidean distance formula, as shown below:

$$d(A) = \frac{|A - I|}{|F - I|} \times 100 \tag{8}$$

If the calculated similarity distance is less than the set minimum similarity threshold, the dance movement is considered standard; if it exceeds the threshold, the movement is considered non-standard. To ensure the reasonableness and accuracy of the calculation, the system dynamically adjusts the threshold based on the type and complexity of the dance movement, thus providing personalized learning feedback to help the student improve in the dance training process.

When evaluating continuous dance movements, the system first needs to decompose the dance movements to be evaluated into multiple smaller sub-movements, then calculate the similarity index for each sub-movement. These indicators include the joint angles, speed, and amplitude, as well as the order and time intervals of the movements. These detailed data are recorded in the system as standard dance movement data and stored in the database. The system uses built-in accelerometers and gyroscopes to sense the student's motion changes in real time during dance practice, capturing the angles, motion speed, and acceleration of each joint. Based on this data, the system calculates the precise indicators of each decomposed dance movement. The system not only evaluates the standardization of the dance movement but also assesses the student's performance based on the movement's timing and rhythm. After the standard dance movement data is input into the system, it forms a set of standardized motion templates for subsequent movement evaluation.

2.3 Improvement of dance movement recognition for students

The goal of this paper is to develop a dance movement assistive evaluation system based on deep learning, enabling students to obtain a personalized dance learning path that is more suitable for them. This paper makes important improvements to the graph convolutional network (GCN). Traditional methods use adjacency matrices to capture the spatial relationships between nodes in a graph, but in dance posture recognition, the student's movements and postures have complex changes in both space and time. To improve the model's performance, this paper introduces the attention mechanism to optimize the Laplacian matrix, allowing the GCN to more accurately learn the relationships between key points, thereby improving its ability to extract spatial features of dance movements. Additionally, this paper adopts the idea of partitioning the image into multiple subgraphs, enhancing computational efficiency through block-wise learning, and finally combining these local features via graph convolution to form global features. Figure 2 provides a flowchart of the optimized graph convolution process.

In terms of temporal feature learning, this paper combines temporal convolutional networks (TCN) to enhance the ability to extract time series information. Unlike traditional convolutional neural networks (CNN), TCN captures information over a larger time range through dilated convolutions, thus avoiding the limitations imposed by the size of the convolution kernel. In dance movement evaluation, temporal features are crucial for dynamic changes in the movements, especially when evaluating the rhythm, duration, and comparison of the student's movements with the standard movements. The advantages of TCN are fully demonstrated in this context. To maintain the stability of the overall feature quantity, this paper sets an appropriate stride in the network to avoid excessive expansion of the key joint feature vectors. Figure 3 illustrates the dilated convolution of TCN. Specifically, let the output be represented by d_{OUT}, the adjacency matrix by X, the identity matrix by U, and the spatial matrix required for learning by Q; then the graph convolution formula used in the GCN is as follows:

$$d_{OUT} = \Gamma^{-\frac{1}{2}}(X+1)\Gamma^{-\frac{1}{2}}d_{IN}Q \tag{9}$$

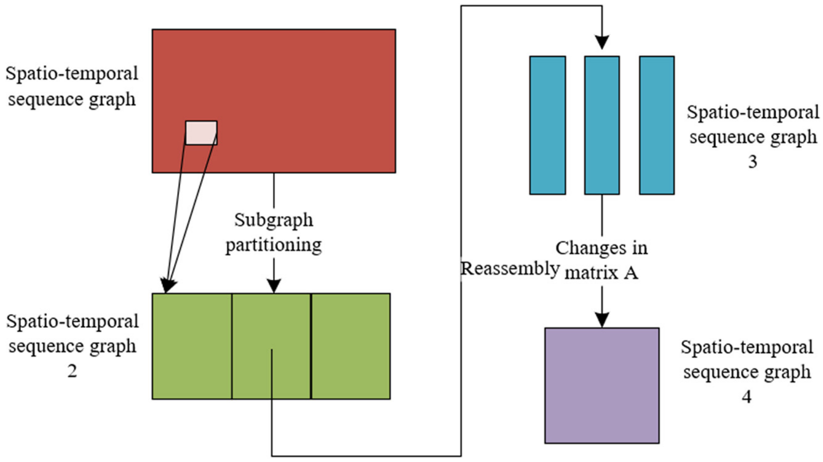

Fig. 2. Optimized graph convolution process diagram

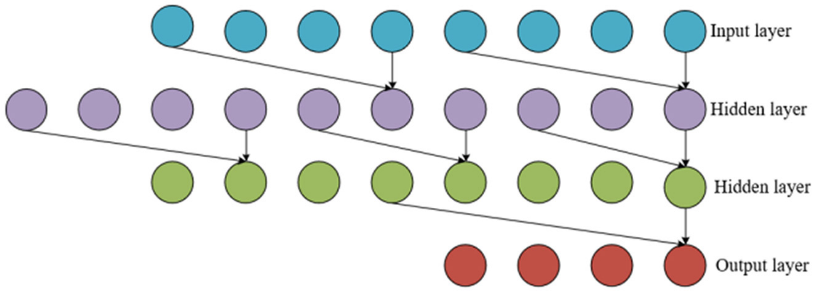

Fig. 3. TCN dilated convolution diagram

3 COLLABORATIVE FILTERING RECOMMENDATION FOR PERSONALIZED LEARNING PATH OPTIMIZATION

Traditional collaborative filtering recommendation methods primarily rely on the calculation of similarity between users when selecting user neighbors. This is often influenced by the method of calculation, similarity metric standards, and the choice of the *k*-value. However, in practical applications, relying solely on user similarity sorting and selecting the top *k* neighbors often fails to accurately reflect the true needs of users, and the choice of *k*-value usually does not achieve the optimal result. Therefore, to improve the accuracy of personalized dance learning content recommendations, this paper proposes an optimization method based on secondary screening, aiming to enhance the accuracy and effectiveness of the recommendation system in learning path optimization through a more rigorous neighbor selection process.

The specific implementation steps include, in the candidate neighbor set, performing secondary screening based on comprehensive similarity. This comprehensive similarity not only considers the student's dance movement evaluation but also incorporates multidimensional information such as their learning progress and learning preferences, thereby more accurately selecting neighbors that are similar to the target across multiple dimensions. This secondary screening process, combined with student data collected from mobile devices, ensures that the recommendation system can recommend more precise and expected learning content based on the user's personalized needs and learning goals, providing students with an optimized personalized learning path. Suppose the similarity between student action i and standard action n is represented by $SIM_{INT}(i,n)$, the threshold coefficient by α, and the average similarity between i and other standard actions by $SIM_{INT}(i,u)$, then the neighbor must satisfy the following formula:

$$SIM_{INT}(i,n) \geq \alpha * \overline{SIM_{INT}(i,u)} \tag{10}$$

Based on the similarity values calculated between each standard dance movement and multiple student learning movements, these similarity values can be used to predict the student's rating for dance movements not yet learned. Specifically, the predicted rating can be calculated by performing a weighted average of the similarities between the student and the standard movements. Suppose the similarity between student i and standard action n is high, then the student's rating for a certain dance type u can be predicted by weighted summing the similarities with other standard movements. In general, the formula for predicting ratings can be expressed as:

$$e'_{iu} = \overline{e}_i + \frac{\sum_{n \in I} SIM(i,n) * (e_{nu} - \overline{e}_n)}{\sum_{n \in I} SIM(i,n)} \tag{11}$$

Where e'_{iu} is the predicted rating of student i for standard movement u, $SIM(i,n)$ is the similarity between student i and standard movement n, $\overline{e}_i$ is the rating of standard movement I by previous learners, and $\overline{e}_n$ is the rating of standard movement I by previous learners. Through this weighted averaging method, the target student i's rating can be predicted based on the similarity with the standard movements and the ratings given by other learners for those standard movements, thereby recommending the most suitable dance movements for the student's current learning progress and ability.

Finally, based on the similarity calculations and predicted ratings between the student and the standard movements, the system can recommend the most appropriate dance movements based on each student's personalized learning needs and progress, optimizing their learning path and improving learning effectiveness. Through this collaborative filtering method, the system can effectively combine the student's learning progress with the characteristics of the standard movements, ensuring the accuracy and personalization of the recommended content.

4 EXPERIMENTAL RESULTS AND ANALYSIS

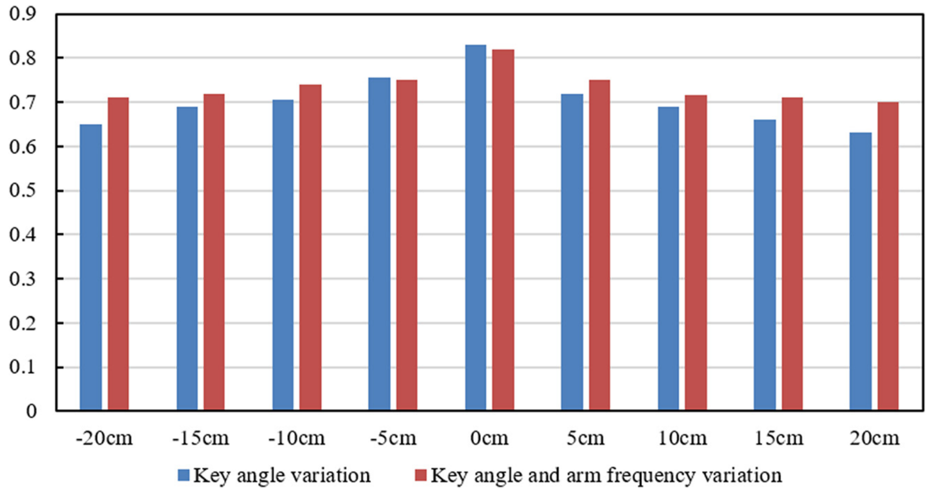

Fig. 4. Comparison of dance action similarity with and without considering arm swing frequency

From the experimental data shown in Figure 4, regarding key angle variations, when the key angle changes from –20 cm to 0 cm, the value shows an upward trend, gradually rising from 0.65 to 0.83. Then, in the range from 0 cm to 20 cm, the value decreases, dropping to 0.63. However, when considering the change in key angles and arm swing frequency, the overall values are relatively stable, with most data fluctuating between 0.7 and 0.75. At 0 cm, the values for both cases reach relatively high values, 0.83 and 0.82, respectively. From this, it can be concluded that the arm swing frequency has a certain impact on the similarity of dance actions. The significant fluctuation in key angle change data indicates that without considering arm swing frequency, the dance action similarity is significantly affected by the key angle, and changes in the key angle may greatly alter the motion shape. On the other hand, when considering the change in arm swing frequency, the data is more stable, suggesting that incorporating arm swing frequency helps maintain a relatively stable dance action similarity under different key angles. This is of great significance for dance posture recognition and evaluation.

In the comparative experiment before and after the improvement of dance posture recognition, the misrecognition situation for various dance actions showed significant changes. As seen in Figure 5, taking hand-foot coordination actions and body rhythm actions as examples, the number of misrecognized hand-foot coordination actions was nine before the improvement, which decreased sharply to five after the improvement, reducing the misrecognition rate by approximately 44.4%. For body rhythm actions, the misrecognition count was as high as 10 before the improvement, but only 2 after the improvement, resulting in a decrease in the misrecognition rate by 80%. Additionally, for rotation movements and other unlisted dance actions, the misrecognition rate decreased to varying degrees. This data clearly indicates that the improved dance posture recognition system has made a qualitative leap in accuracy. Based on the experimental results above, we can conclude that the significant success of this improvement is primarily due to the focus on the dance movements themselves, particularly in the key point feature extraction stage, where the key nodes of the dance movements are precisely anchored, significantly enhancing the recognition accuracy.

type	Rotation	Combination of footwork and body rhythm	Body wave	Limb swing	Hand and foot coordination
Rotation	186	0	0	9	5
Combination of footwork and body rhythm	0	190	6	4	0
Body wave	0	0	192	3	5
Limb swing	2	3	5	184	6
Hand and foot coordination	10	4	1	3	182

(a) Confusion matrix before dance posture recognition improvement

Fig. 5. *(Continued)*

type	Rotation	Combination of footwork and body rhythm	Body wave	Limb swing	Hand and foot coordination
Rotation	190	0	0	5	5
Combination of footwork and body rhythm	0	195	0	5	0
Body wave	0	0	198	2	0
climb	2	0	3	193	2
Hand and foot coordination	2	0	3	3	192

(b) Confusion matrix after dance recognition improvement

Fig. 5. Comparison of confusion matrix before and after dance posture recognition improvement

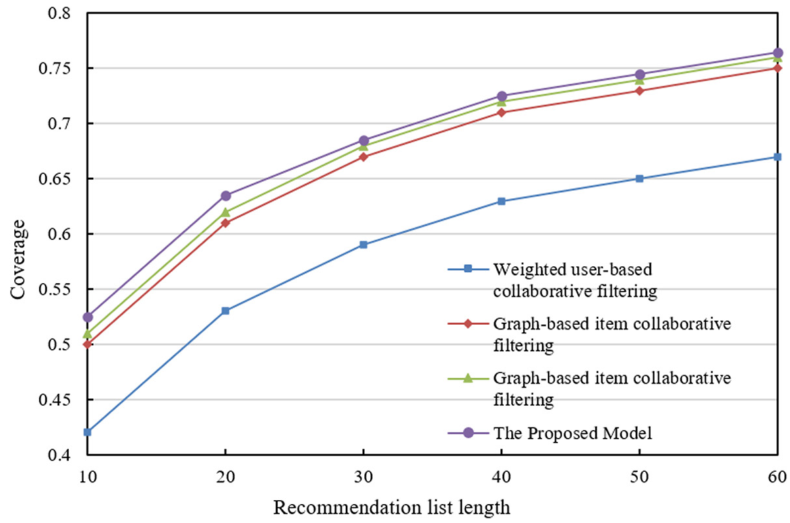

Fig. 6. Comparison of personalized learning content recommendation coverage of different types of collaborative filtering algorithms

From the data provided in Figure 6, which compares the personalized learning content recommendation coverage of different collaborative filtering algorithms at different recommendation list lengths, it can be seen that as the length of the recommendation list increases, the recommendation coverage of each algorithm shows a gradual upward trend. The coverage of weighted user-based collaborative filtering increases steadily from 0.42 at a list length of 10 to 0.67 at a list length of 60. The graph-based item collaborative filtering increases from 0.5 to 0.75, also showing a relatively stable growth curve. The multi-layer perceptron algorithm's recommendation coverage increases from 0.51 to 0.76, showing a certain advantage. In comparison, the proposed content-based collaborative filtering recommendation algorithm in this paper has a recommendation coverage that increases from 0.525 to 0.765, which is superior to both the weighted user-based collaborative filtering and the graph-based item collaborative filtering at all recommendation list lengths and is close to the performance of the multi-layer perceptron algorithm, demonstrating a more ideal recommendation coverage.

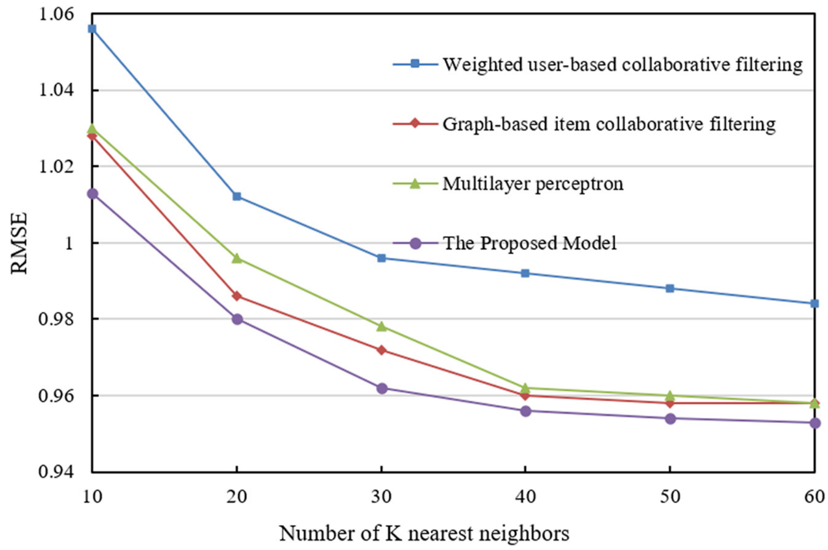

Fig. 7. RMSE values of personalized learning content recommendation using different collaborative filtering algorithms at different K-nearest neighbors

According to the RMSE values for personalized learning content recommendation at different K-nearest neighbors provided in Figure 7, it can be observed that as the K value increases, the RMSE values for all algorithms generally show a downward trend, indicating that the recommendation error gradually decreases and the recommendation accuracy improves. Specifically, for the weighted user-based collaborative filtering, the RMSE value decreases steadily from 1.056 to 0.984 as the K value changes from 10 to 60. The graph-based item collaborative filtering shows a more significant decrease in RMSE, from 1.028 to 0.958, but the RMSE value stabilizes after the K value increases to 50. The multi-layer perceptron algorithm's RMSE value decreases from 1.03 to 0.958, showing a similar trend to that of the graph-based item collaborative filtering, with a smaller error. The RMSE value for the proposed method in this paper decreases from 1.013 to 0.953, remaining stable overall, and showing slightly lower error values than the weighted user-based collaborative filtering and graph-based item collaborative filtering at all K values, though it is similar to the multi-layer perceptron.

5 CONCLUSION

The research objective of this paper is to explore how mobile applications can optimize personalized learning paths in dance education. Two main research directions are proposed. First, a dance posture assessment method based on intelligent technology is designed to assist students in personalized learning evaluations at different learning paces. Through posture recognition technology, the system can assess students' dance movements in real-time and adjust learning content based on each student's progress. Second, this paper proposes a learning content-based collaborative filtering recommendation algorithm aimed at optimizing students' learning paths. By analyzing students' learning history, it recommends the most suitable learning content to help students master dance skills more efficiently. In the experimental process, several collaborative filtering recommendation algorithms are compared, and the results show that the learning content-based collaborative filtering method outperforms traditional methods in recommendation accuracy and error control. Experimental results indicate that this recommendation algorithm can accurately identify students' learning needs and provide personalized recommendations, thereby improving learning effectiveness and efficiency. Especially when adjusting the recommended content and learning paths, it can better adapt to the learning pace of different students, reducing ineffective learning.

This study provides new ideas and methods for personalized learning paths in dance education, with high practical value. Through mobile application technology, teachers can more accurately grasp students' learning status, and students can receive tailored learning suggestions. However, the study also has certain limitations. Firstly, the limitation of data volume and sample size may affect the universality of the algorithm's recommendations. Secondly, there is room for improvement in the accuracy and real-time performance of posture assessment technology, especially in recognizing complex movements. Future research can focus on the following aspects: 1) Improving the precision of posture assessment technology, especially in real-time evaluation of complex dance movements; 2) further optimizing the recommendation algorithm by increasing the learning data from more students, improving its adaptability and accuracy; and 3) exploring more personalized teaching models, combining virtual reality and other technologies to provide a more immersive and interactive learning experience.

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