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Exploring the Impact of Badminton Core Strength Training Incorporating Deep Learning Algorithms on Footwork Agility

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Abstract Currently, traditional sports equipment and technical solutions in higher education institutions are unreasonable, and outdated management models for sports training fail to provide scientific guidance for badminton athletes, resulting in suboptimal overall training outcomes. This paper develops a comprehensive contactless motion recognition system based on deep learning algorithms. The system utilizes the Microsoft Kinect V2 smart camera to accurately capture the three-dimensional spatial positions of human skeletal joint points in real time and convert them into motion data streams. Additionally, the DTW algorithm is used to calculate the joint angle differences between standard motion sequences and test motion sequences, and an action evaluation formula is defined to assess core strength training movements. After testing, the system's accuracy in evaluating movement results ranges from 90.20% to 94.69%, enabling effective assessment of core strength training movements. After applying the system to badminton core strength training, students' foot flexibility significantly improved compared to conventional core strength training ($P < 0.05$). Therefore, teachers can actively apply the motion recognition system in core strength training when conducting badminton instruction

Index Terms motion recognition system, Kinect V2, DTW, foot flexibility

I. Introduction

Badminton, as a fast-paced, explosive, and highly technical competitive sport, places extremely high demands on athletes' physical fitness and technical skills [1]. During badminton matches, athletes' body postures are constantly changing, and they must perform rapid braking and quick stops in response to shifts in their opponents' and their own offensive and defensive strategies [2]. Therefore, for badminton, whether it is for competitive play, as a fitness activity, or for teaching purposes, footwork training must be given priority [3]-[5]. Rapid and reasonable footwork mobility, along with efficient hitting techniques, are critical factors influencing the outcome of a match, particularly during offensive-defensive transitions, which demand high levels of body center of gravity control and posture control [6]-[8]. Core strength training is a coordinated training method based on body center of gravity movement, which scientifically trains the muscles attached to the lumbar spine, pelvis, and hip joints. It has a positive effect on improving the stability and power of badminton footwork [9]-[12].

On one hand, conducting core strength training in badminton helps enhance the balance and stability of the core muscle groups in badminton athletes [13]. In badminton, athletes are primarily in defensive or offensive states, with their body positions constantly adjusting based on the opponent's direction. This requires effective coordination between the upper and lower limbs, as well as the ability to generate force and move efficiently. To fully harness the power of upper and lower limb movements, it is essential to strengthen core strength training [14]-[17]. On the other hand, core strength training in badminton helps reduce exercise fatigue and prevent or reduce sports injuries [18]. Core strength training helps enhance athletes' awareness, strengthen deep muscle groups, and support the entire body through force transmission, thereby delaying and alleviating fatigue and preventing or reducing sports injuries [19]-[22]. However, in traditional core strength training, students often lack a deep and comprehensive understanding of the training content, making it difficult for them to accurately identify the specific causes of their movement deficiencies [23], [24]. Focusing solely on strictly adhering to theoretical training can make the otherwise enjoyable sport of badminton monotonous and even become a source of aversion for students [25], [26]. Therefore, in badminton footwork instruction, core strength training should emphasize innovative methods and approaches.

Badminton is not a sport that relies on a single joint or muscle group; it requires the coordinated activation of multiple muscle groups working together. Core strength training can engage more parts of the body in the movement, enhancing an athlete's balance and stability. Based on this, numerous scholars have studied the relationship between athletes' core strength and agility. Savla, H. N., et al. pointed out that core muscle strength can enhance muscle coordination between the upper and lower limbs during movement, while agility is an essential element for quickly executing high-intensity movements, and the two are correlated [27]. Sm, F, and others emphasized that balance, agility, and core strength are key factors in improving athletes' badminton-specific skills, and core strength training can effectively enhance athletes' dynamic balance, flexibility, and footwork, directly promoting the improvement of their badminton-specific skills [28]. Wang, T, et al. outlined the significant role of resistance training in improving athletes' competitive performance. Core strength training enhances badminton athletes' strength, speed, agility, and endurance while reinforcing technical stability and force transmission within the kinetic chain [29]. Naveen, M, et al. assessed the effects of core stability training and jump training on athletes' dynamic balance, endurance, and agility. Core strength training promotes the development of core muscles, thereby enhancing athletes' competitive performance [30]. Ihsan, F, et al. also used leg movement testing instruments to collect data on athletes' muscle endurance, finding that athletes with higher muscle endurance exhibited greater agility [31]. Borkar, P validated through empirical research that a core stability exercise program can significantly improve dynamic balance and agility in amateur badminton athletes [32]. Shetty, S et al. demonstrated that core muscle group training can enhance athletes' movement balance and agility, and that athlete training programs incorporating targeted core strength training content can further improve athletic performance [33]. The above studies indicate that strengthening core muscle strength can improve athletes' physical stability and balance during movement, enabling them to better handle various complex movements and competition scenarios. Additionally, developing targeted core strength training content can further optimize movement coordination and force efficiency.

Some scholars have attempted to incorporate smart technology to optimize core strength training programs. Huang, W, and Zhang, F investigated the combined application of core strength training and badminton footwork training, utilizing computer technology to standardize athletes' foot movements and body coordination during training, thereby further enhancing training effectiveness [34]. Liu, G found a certain correlation between badminton athletes' core strength training data and their footwork flexibility, and employed deep learning methods for analysis and validation, effectively predicting athletes' footwork flexibility [35]. Ma, S, et al. used machine learning (ML) technology to analyze the relationship between core training and athletic performance in badminton athletes, optimizing training content to enhance athletes' stability, agility, and strength training outcomes [36]. However, the aforementioned technologies face numerous athletic metrics, and their physical training plans and programs are not sufficiently scientific, reasonable, or systematic, necessitating further research to enhance the scientific rigor and effectiveness of training.

This paper proposes an intelligent motion recognition system based on deep learning algorithms. The system first uses a KinectV2 smart camera to collect human skeletal data. It then matches the extracted features with data in the gait library to achieve user motion recognition. The skeletal coordinates are then converted into joint angles, and the DTW algorithm is used to match the test sequence of core strength training movements with the standard sequence, calculating the DTW distance between joint angles. This is used as an experimental parameter to define a set of movement evaluation formulas, enabling the assessment of core strength training movements. Finally, to verify the impact of the system on the footwork flexibility of badminton athletes after implementation, a control experiment was designed. The hexagonal agility test, T-shape run test, and defensive footwork movement test were selected to explore the extent of the impact.

II. Research on a deep learning-based badminton core strength training system

II. A. Training motion recognition

II. A. 1) Gait Recognition

With the rapid development of human civilization, traditional identification technologies can no longer meet the growing needs of society. In this context, gait recognition technology has emerged. Gait recognition is a biometric identification technology that uses human behavioral characteristics to identify human movements. The steps of gait recognition are as follows:

(1) Capture video.

(2) Preprocess the target video.

(3) Extract target contour features from the obtained images based on real-world conditions.

(4) Match the extracted features with data in the gait database.

The 3D position information of human skeletal joints can serve as reference points for motion recognition. By combining the 3D coordinates of the 25 skeletal joints tracked and captured by KinectV2 into a skeletal template, gait data sequences are obtained. After preprocessing and analyzing the user's gait features, the skeletal template samples are compared with the user poses previously set in the system to determine the user's intent, thereby achieving user motion recognition.

II. A. 2) Kinect Recognition Analysis

The system utilizes Microsoft's Kinect [37] 3D camera sensor. Its primary advantages include real-time capture of experimental motion scenes, efficient identification and transmission of skeletal information, and voice recognition capabilities for users. The Kinect primarily consists of an RGB camera, an infrared receiver and transmitter for depth imaging, and a microphone array.

The ability of Kinect to capture motion scenes in real time primarily relies on the infrared camera, infrared projector, and color camera. Kinect emits infrared light with a wavelength of 830 nm through the infrared emitter, which is then received by the infrared receiver. The infrared light is encoded and decoded, and depth images are generated frame by frame. Depth images are processed through background separation and human recognition algorithms to obtain corresponding color images from the RGB camera. Kinect transmits these image data to the application for processing.

In summary, the Kinect V2 device offers numerous advantages over ordinary cameras. The main drawback of ordinary cameras is their overreliance on color images, which makes it difficult to eliminate environmental influences on experimental data. In contrast, the Kinect V2 relies on depth images for motion skeleton recognition and analysis, thereby effectively mitigating environmental influences.

II. B. Action evaluation based on the DTW algorithm

II. B. 1) Dynamic Time Warping Algorithm

The Dynamic Time Warping (DTW) algorithm is an algorithm used to calculate the optimal match between two sequences, commonly employed for similarity measurement. It is primarily applied in fields such as speech recognition and biometric identification. In this paper, since the dimensions of the two action sequences may differ, this algorithm is adopted to assess the similarity between the two action sequences [38].

Consider the two time series curves B and D shown in Figure 1. Applying the concept of time series to action sequences, curves B and D are represented by Equations (1) and (2):

$$B = (B_1, B_2, ..., B_i, ..., B_m) \tag{1}$$

$$D = (D_1, D_2, ..., D_j, ..., D_n) \tag{2}$$

In the equation, B represents the test sequence, D represents the standard sequence, m and n represent the number of frames in the two action sequences, B_i represents the feature vector of the i th frame, and D_j represents the feature vector of the j th frame. If m and n are equal, the cumulative distance between the two action sequences is calculated directly. When m and n are unequal, the DTW algorithm is used to align the two action sequences. Specifically, the two sequences are constructed into an $m \times n$ matrix, where the element (i, j) in the matrix represents the distance $d(B_j, D_j)$ between the corresponding points B_i and D_j of the two action sequences. This distance can be measured using different metrics depending on the specific situation; here, the Euclidean distance is used, as shown in Equation (3):

$$d(B_j, D_j) = \sqrt{\sum_{w=1}^{N} (B_{iw} - D_{jw})^2} \quad 1 \le w \le N \tag{3}$$

In the equation, B_{iw} and B_{jw} represent the eigenvalues of frames i and j in action sequences B and D, respectively, and N represents the dimension of the action sequence.

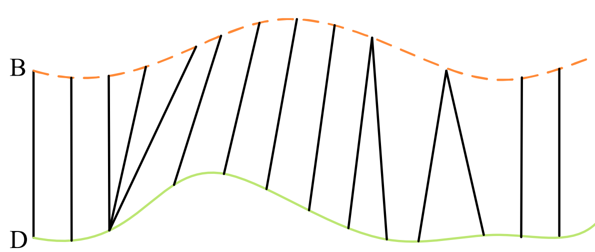


Figure 1: Time Series

The core idea of the DTW algorithm is to find the best matching path between two time series by comparing the distance between each point in the two time series. This path is defined as a regular path [39] and is represented by W, which is the best path from point (1, 1) to point (m,n). The regular path is shown in Figure 2.

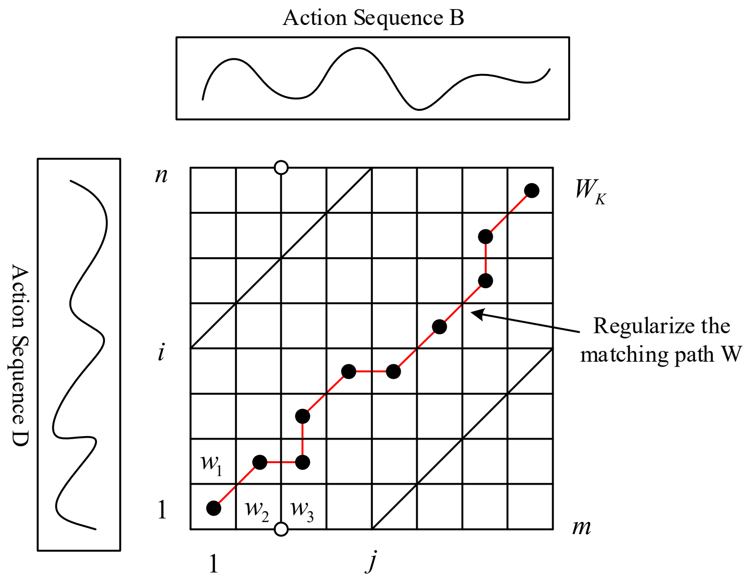


Figure 2: Straightening the path

W is a continuous set of matrix elements that defines the mapping between B and D. The k th element of W is defined as $w_k = (i,j)_k$, so W can be expressed by equation (4):

$$W = \{w_1, w_2, ..., w_k, ..., w_k\} \quad \max(m,n) \le k \le m+n-1 \tag{4}$$

A dynamic regular path must satisfy three conditions:

(1) Boundary conditions: Specify the starting point of the regular path as $W_1 = (1,1)$ and the endpoint as $W_k = (m,n)$.

(2) Continuity condition: If $W_{k-1} = (a,b)$, then $W_k = (a^{'}, b^{'})$, where $(a^{'} - a) \le 1$ and $(b^{'} - b) \le 1$ must be satisfied, ensuring that there are no gaps between adjacent points.

(3) Monotonicity condition: If $W_{k-1} = (a,b)$, then $W_k = (a^{'}, b^{'})$, which must satisfy $(a^{'} - a) \ge 1$ and $(b^{'} - b) \ge 1$, restricting the points on the regular path to progress monotonically over time.

After the above three conditions are satisfied, each grid point path has three remaining directions. If the path passes through grid point (i,j), then the next grid point it passes through can only be one of $(i+1j),(i,j+1), or(i+1,j+1)$.

To obtain the optimal regular path, define the cumulative distance $A(i,j)$ as the sum of $d(B_j, D_j)$ and the distance to the nearest element that can reach this point, as shown in Equation (5):

$$A(i,j) = d(B_i, D_j) + min\{A(i-1,j-1), A(i,j-1), A(i-1,j)\} \tag{5}$$

The optimal path is the path that minimizes the cumulative distance along the path. The smaller the cumulative distance, the greater the similarity between the two action sequences.

II. B. 2) Conversion of skeletal coordinates to joint angles

To evaluate the training movements, skeletal coordinates are converted into joint angles. To reduce the computational load while maintaining an accurate representation of the movements, this paper selects joint angles for eight joints: the left shoulder, left elbow, right shoulder, right elbow, left knee, left hip, right knee, and right hip. The joint angle at the left knee is represented by the angles at the left hip, left knee, and left ankle, denoted as θ_{lk}, and similarly, the joint angles at the left shoulder, left elbow, right shoulder, right elbow, left hip, right knee, right hip are denoted as $\theta_{ls}, \theta_{le}, \theta_{rs}, \theta_{re}, \theta_{lc}, \theta_{rk}, \theta_{rc}$, respectively. The joint angle diagram is shown in Figure 3. Taking the angle of the left knee joint as an example, calculating this angle requires the coordinate data of the left hip, left knee, and left ankle. The coordinates of the left hip are denoted as $LC(LC_x.LC_y)$, the coordinates of the left knee are denoted as $LK(LK_x, LK_y)$ denotes the coordinates of the left knee, and $LA(LA_x, LA_y)$ denotes the coordinates of the left ankle. Then, the direction vectors of the joint nodes are denoted by $LC\_LK(LC_x - LK_x, LC_y - LK_y)$ and $LK\_LA(LK_x - LA_x, LK_y - LA_y)$ represent the direction vectors of the joint nodes. The angle is solved using the cosine theorem, as shown in Equation (6):

$$\theta_{lk} = \arccos\left(\frac{LC}{|LC_L K| \, LK_L A}\right) \quad 0^{\circ} \le \theta_{lk} \le 180^{\circ} \tag{6}$$

Define a feature vector c_i to represent the 8 joint angle features in a frame image, as shown in Equation (7):

$$c_i = [\theta_{ls}, \theta_{le}, \theta_{rs}, \theta_{re}, \theta_{lk}, \theta_{lc}, \theta_{rk}, \theta_{rc}] \tag{7}$$

An action sequence has multiple frames of images. Define K as the set of joint angle features of all frames of images, as shown in Equation (8):

$$K = [c_1, c_2, c_3, ..., c_n] \tag{8}$$

In the formula, n is the total number of frames contained in the action sequence.

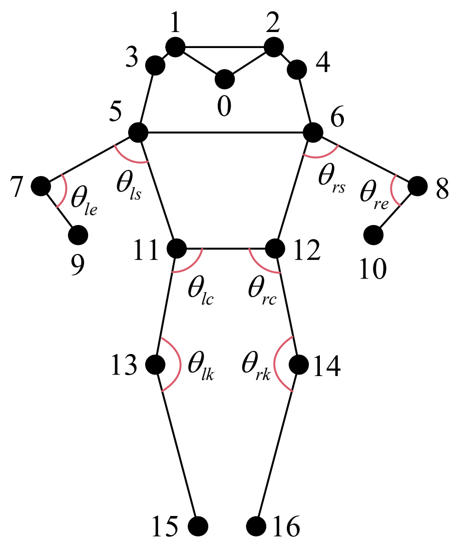


Figure 3: Schematic diagram of joint angles

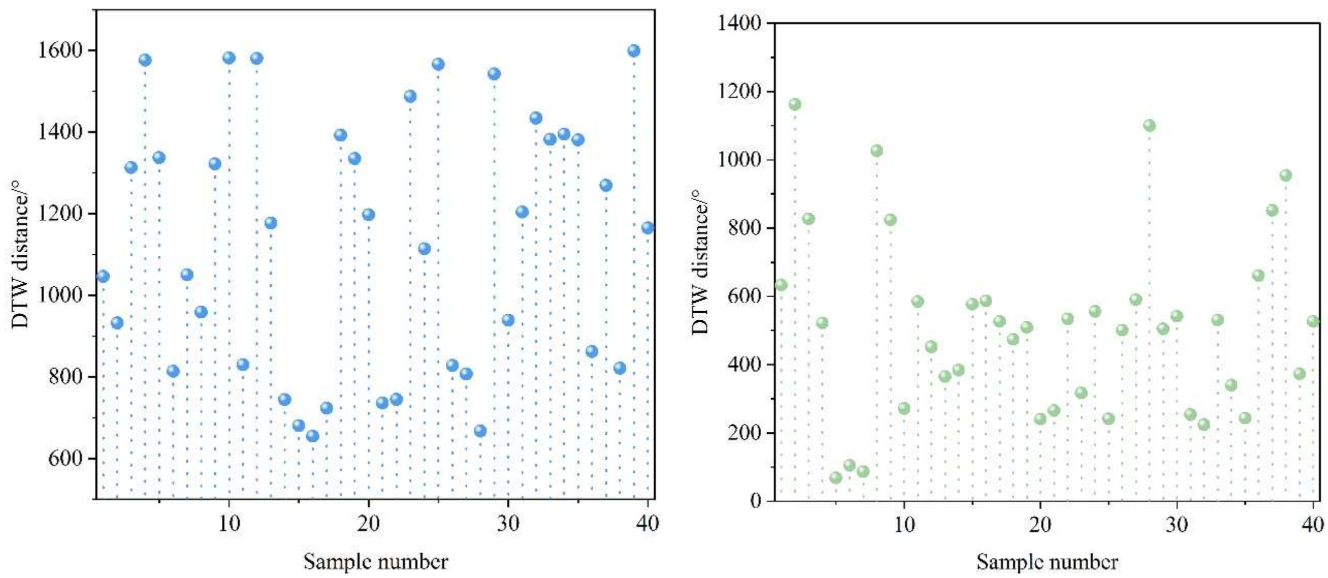
II. B. 3) Experiments and Analysis of Results

The purpose of motion evaluation analysis is to compare the motion sequence being evaluated with a standard motion sequence and assess the quality of the sequence (i.e., determine how well the motion was performed). Traditional methods involve manual observation by experienced coaches, referees, and other experts who identify differences in the motions and assign scores. However, scoring results are influenced by subjective factors, so computers are needed to assist humans in scoring by utilizing similarity analysis. Action data assessment based on RGB video is not sufficiently accurate, so using skeletal data for scoring has certain advantages.

This paper uses the DTW algorithm introduced above to calculate the DTW distance between the test action sequence and the standard action sequence as a similarity assessment parameter. To reduce the computational load, eight joint angle features were selected as feature parameters: right shoulder, right elbow, left shoulder, left elbow, right hip, right knee, left hip, and left knee. The first action, “sealed like a book,” from the eight actions in the dataset is selected as the evaluation object. Forty samples are selected as the test action sequence, and the action video data of sports major students is used as the standard action sequence template.

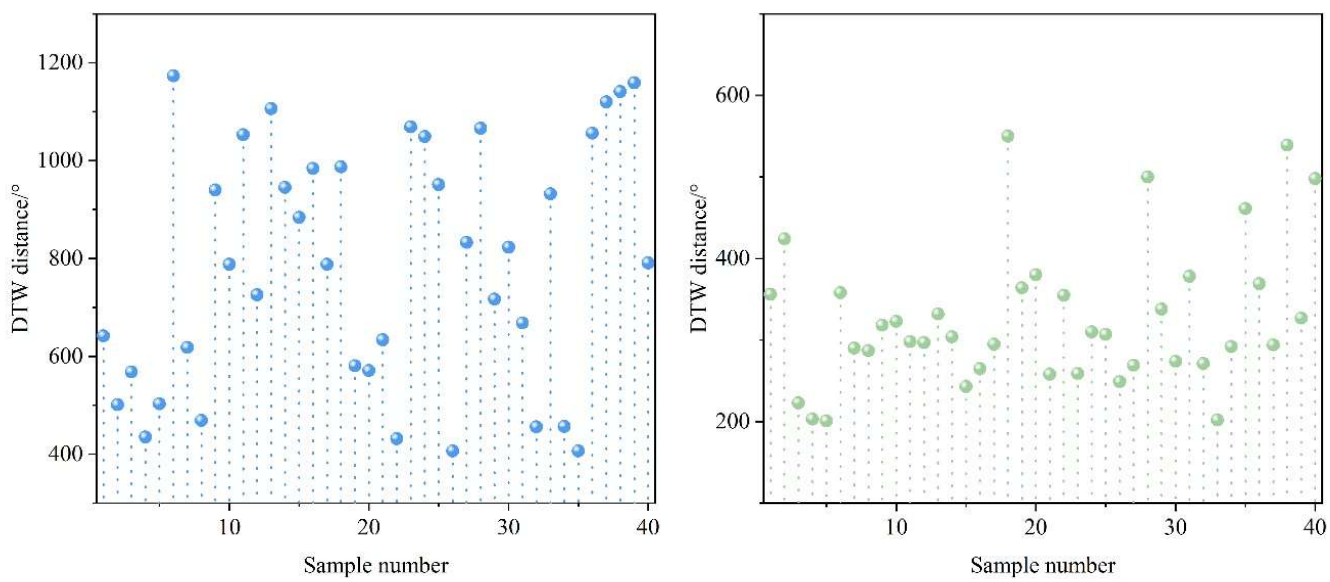
This paper observes the distribution of joint angle distances through multiple calculations. The DTW distance distributions for the left elbow and left knee are shown in Figure 4, where (a) and (b) represent the DTW distance distributions for the left elbow and left knee, respectively. As shown in the figure, the DTW distances for the left elbow angle are mostly distributed between 600 degrees and 1400 degrees, with a small portion distributed between 1400 degrees and 1600 degrees. The DTW distances for the left knee angle are mostly distributed between 0 degrees and 600 degrees, with a small portion distributed between 600 degrees and 1200 degrees.

The DTW distance distribution for the left shoulder and left hip is shown in Figure 5, with (a) and (b) representing the DTW distance distributions for the left shoulder and left hip, respectively. As can be seen from the figure, the DTW distances for the left shoulder angle are mostly distributed between 400 degrees and 1000 degrees, with a small portion distributed between 1000 degrees and 1200 degrees. The DTW distances for the left hip angle are primarily distributed between 200 degrees and 400 degrees, with a small portion distributed between 400 degrees and 600 degrees. Values outside these intervals are discarded.



(a) Left elbow (b) Left knee

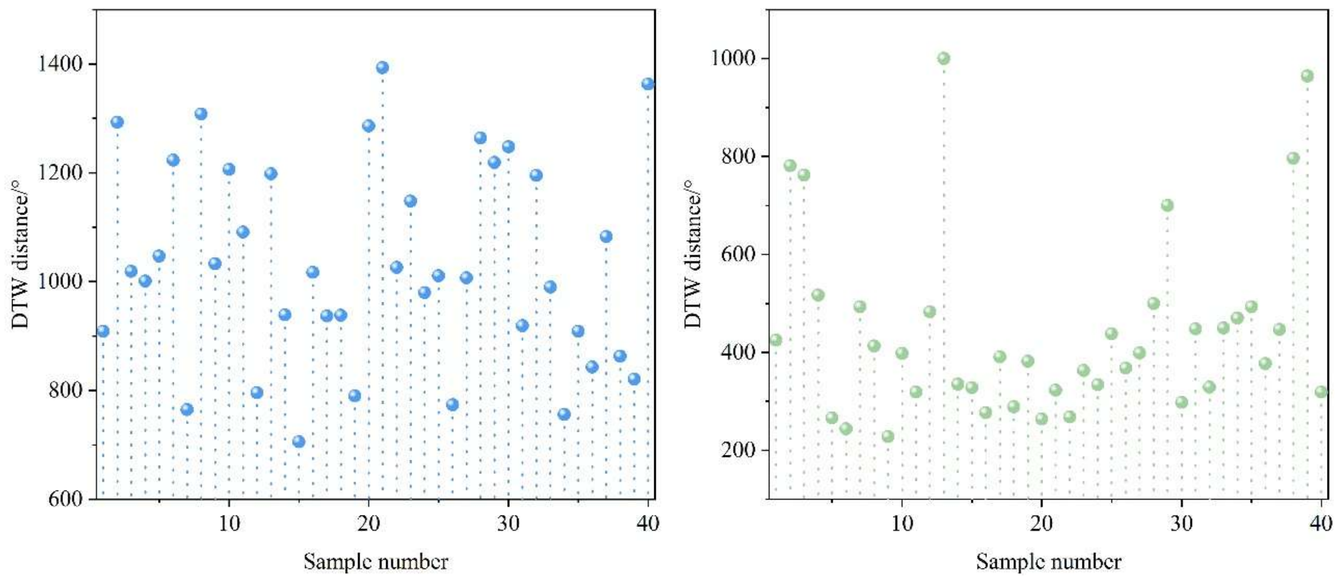
Figure 4: The DTW distance of the left elbow and the left knee



(a) Left shoulder (b) Left hip

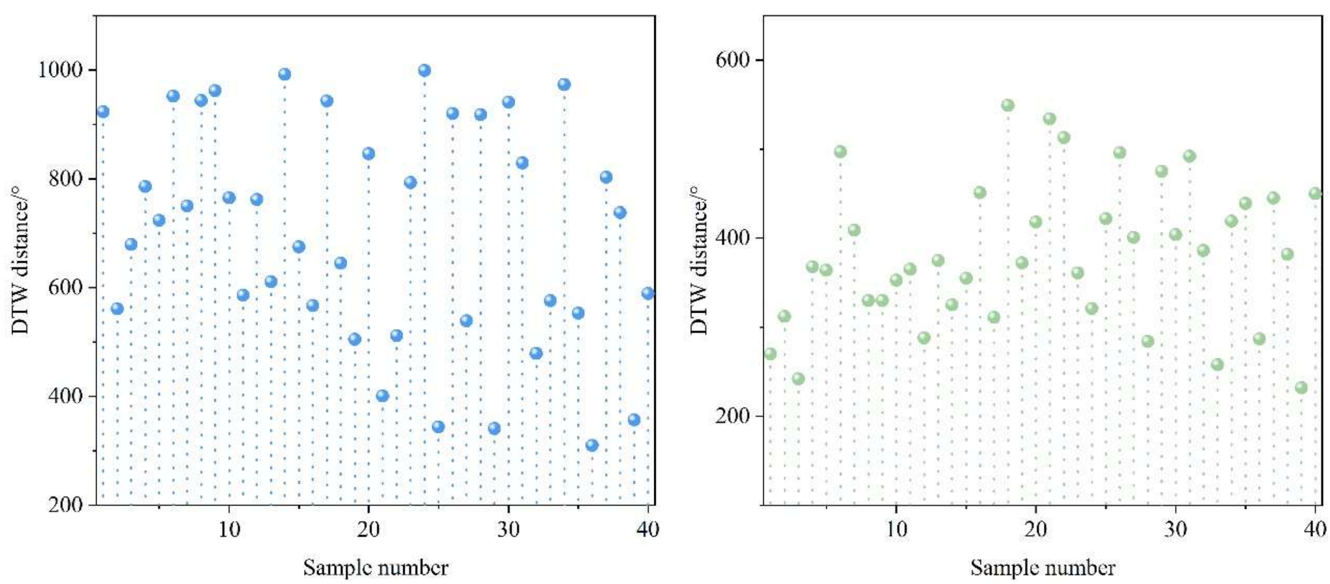
Figure 5: The DTW distance of the Left shoulder and the Left hip

The DTW distance distributions for the right elbow and right knee are shown in Figure 6, where (a) and (b) represent the DTW distance distributions for the right elbow and right knee, respectively. The DTW distance distributions for the right shoulder and right hip are shown in Figure 7, where (a) and (b) represent the DTW distance distributions for the right shoulder and right hip, respectively.



(a) Right elbow (b) Right knee

Figure 6: The DTW distance of the Right elbow and the Right knee



(a) Right shoulder (b) Right hip

Figure 7: The DTW distance of the Right shoulder and the Right hip

Figures 4 to 7 show that the distances between the four joints of the upper limbs are relatively sparse, while those between the four joints of the lower limbs are relatively dense, indicating that the upper limbs have a larger range of motion.

Based on the above experimental analysis, an evaluation method was developed for movements such as "sealing and closing," as shown in the following formula:

$$s_a = s_c - (d_1 - d_2) \times f_c \tag{9}$$

In the equation, s_a represents the score for an angle feature, s_c represents the score for angle allocation, which is 12.5. d_1 represents the DTW distance value, and d_2 represents the minimum value within the effective interval of the DTW distance. f_c is the loss parameter, whose value is related to the magnitude of the action change. Joints with larger magnitude have smaller loss parameters, while those with smaller magnitude have larger loss parameters. The final total score is the sum of the scores for the 8 joint angles, i.e.:

$$S = \sum_{\alpha=1}^{8} S_{\alpha} \tag{10}$$

The DTW distance and loss parameters are shown in Table 1.

Table 1: DTW distance and loss parameter value table

Angle	DTW distance	Loss parameter
Right knee	230	0.415%
Left knee	200	0.433%
Right shoulder	400	0.357%
Left shoulder	500	0.311%
Right elbow	800	0.276%
Left elbow	700	0.246%
Right hip	250	0.489%
Left hip	250	0.477%

Each joint angle has a DTW distance distribution range. Through multiple experiments, the baseline DTW distances and joint loss parameters for different joint angles were obtained. These values were then substituted into the formula to calculate the action evaluation scores. The results of the action evaluation are shown in Table 2. The DTW distance values corresponding to the eight joints, along with the evaluation scores from this study and the professional scoring results, are provided separately. Each joint node has a total score of 12.5 points, with a maximum score of 100 points. The total evaluation score from this study is 86.1 points, while the professional score is 86.6 points, differing by only 0.5 points, thereby validating the rationality of this action evaluation method.

Table 2: Action evaluation results

Joint Angle name	DTW distance	Evaluation score	Professional rating
Right knee	1168	11.2	11.3
Left knee	1386	10.6	10.6
Right shoulder	450	11.2	12.1
Left shoulder	490	11.2	10.8
Right elbow	591	11	11.2
Left elbow	789	9.9	10.4
hip	992	10.1	10
Left hip	1027	10.9	10.2

II. C. Implementation of the motion recognition system

The technical architecture of this system can be divided into five layers. The Kinect data acquisition layer uses the Kinect smart camera to capture human depth images, human skeleton images, and human color images, and transmits this information in the form of video stream data to the skeleton algorithm processing layer. The algorithm processing layer performs filtering and DTW template matching on this data. Finally, the processed skeleton node data undergoes motion matching in the motion recognition layer, and the results and scores of the motion detection are displayed in the application layer. The framework structure of the motion testing system is shown in Figure 8.

III. System application testing and analysis

III. A. Specific Methods for Core Strength Training for Badminton Players

III. A. 1) Basic exercises without equipment

In badminton competitions, athletes must perform a series of technical movements while moving quickly to overcome their own body weight, which places extremely high demands on their ability to maintain relative stability in an unbalanced state [40]. To achieve this goal, the upper and lower limbs and core muscle groups must work closely together, with the core muscle group serving as the key hub connecting the upper and lower limbs, making its importance self-evident.

Bodyweight training, which involves exercises using only one's own body weight without external equipment, is an effective method for developing core strength in badminton athletes. During the foundational phase of core strength training, the focus is on enhancing athletes' perception and control of core stability through exercises performed in a relatively static state. This process involves activating and strengthening deep core muscle groups, such as the deep muscles on both sides of the waist and abdomen, and the deep muscles on the back of the thighs. Athletes must deeply understand the critical role these muscles play in maintaining body balance and stability.

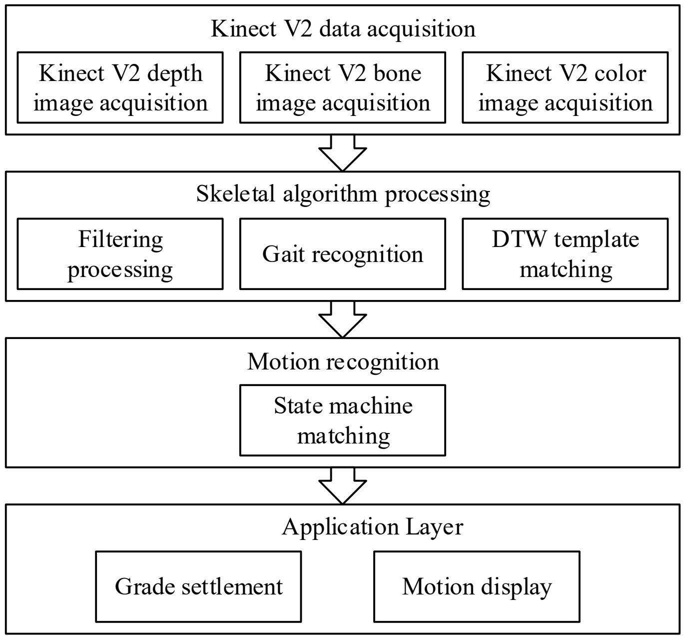


Figure 8: Motion test system framework

The specific methods of foundational training include two main categories: static stretching exercises and dynamic explosive power exercises. Static stretching exercises aim to improve the endurance and stability of core muscle groups through prolonged isometric muscle contractions. For example, the athlete assumes a prone position and uses one arm and the opposite foot to maintain balance. Alternatively, assume a side-lying position and use only the same-side hand and leg to maintain balance. Another option is the “prone double-arm or elbow support abdominal control” method. During these exercises, athletes should focus on breath control, particularly the use of diaphragmatic breathing, to promote muscle relaxation and blood circulation. Dynamic explosive power exercises, on the other hand, focus on enhancing the rapid contraction and explosive power of core muscle groups to adapt to the rapid direction changes and high-intensity physical contact in badminton. Specific exercises such as abdominal leg lifts, supine sit-ups, prone back lifts, supine back bridges, push-ups with clapping, and leg-arm cross two-point lifts can effectively stimulate the core muscle groups, enhancing their rapid response and force output capabilities.

III. A. 2) Agility exercises using equipment

In badminton players' agility training, exercises performed in non-equilibrium states are a critical component for enhancing core motor skills and stability. This training typically relies on specific equipment such as balance boards and Swiss balls, which athletes use to improve their control over body stability and precision, while significantly enhancing their self-awareness. This, in turn, effectively improves their ability to execute high-quality returns during high-speed movements.

Core strength training methods primarily fall into two categories: single-purpose equipment and multi-functional equipment. Single-purpose equipment focuses on using specific unstable devices or bodyweight-based tools to strengthen deep and small muscle groups, while repetitive movements enhance coordination among various muscle groups. In contrast, core strength training using multi-functional equipment is more complex, combining various non-balanced devices (such as balance boards and Swiss balls) with lightweight auxiliary equipment (such as small dumbbells and barbell plates). In this training, athletes must perform various movements such as pushing, stretching, and twisting in unstable conditions, and can integrate badminton-specific techniques into the training to effectively improve their ability to quickly react and precisely execute skills in unstable environments. Through scientifically designed non-equilibrium training combined with diverse equipment usage, athletes can effectively enhance their core stability and agility.

III. B. Analysis of test results

Based on the aforementioned foundational exercises and agility drills, this chapter employs a motion recognition system to conduct systematic testing on the following exercises: abdominal crunch with leg lift (T1), supine sit-up (T2), prone back lift (T3), supine back bridge (T4), push-up clap (T5), leg-arm cross two-point lift (T6), non-balance apparatus exercises (T7), and lightweight assistive apparatus exercises (T8). Ten male and ten female participants were invited to participate in the testing experiment for five consecutive days, yielding 800 test samples. The system's motion recognition rate and the accuracy of motion result evaluations were statistically analyzed. The statistical results are shown in Figure 9. The movement recognition rate ranged from 95.14% to 99.42%, and the accuracy rate of movement result evaluation ranged from 90.20% to 94.69%. The test results indicate that the system has a very high movement recognition rate and that the movement recognition function is highly reliable.

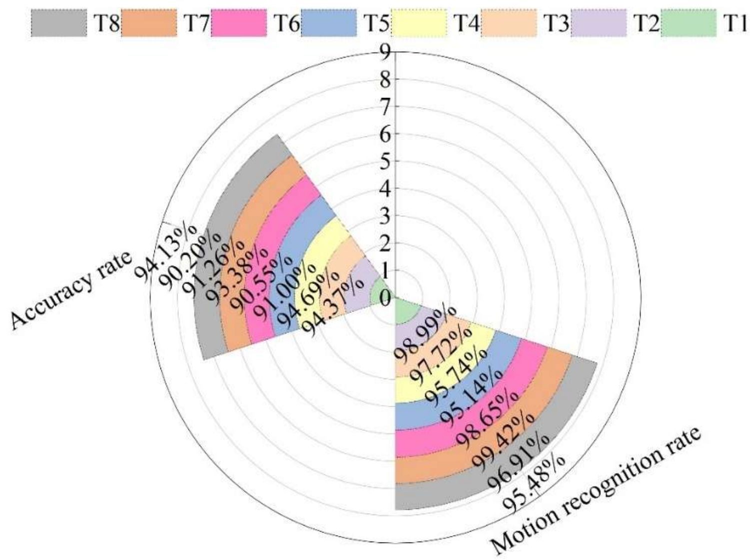


Figure 9: Experimental results

IV. Analysis of foot flexibility assessment experiments

The motion recognition system constructed in the preceding section was applied to the daily core strength training of badminton players to improve the accuracy of core strength training movements. To verify the effectiveness of the motion recognition system, this paper examined the training effects in terms of foot flexibility.

IV. A. Experimental Design

IV. A. 1) Experimental subjects

The subjects of this experiment were students from two classes in the second year of the physical education program at School A. During the experiment, the two classes were randomly assigned by lottery to either the experimental class (using a motion recognition system to assist with core strength training) or the control class (conventional training). A total of 70 students participated in this teaching experiment, with 35 students in each class.

IV. A. 2) Experiment time

The experiment lasted for 14 weeks.

IV. A. 3) Experimental procedure

The experiment was conducted in four phases: grouping, pre-test, intervention, and post-test. In the pre-test and post-test phases, the following three indicators were used to assess badminton footwork flexibility: the hexagonal agility test (T1), the T-run test (T2), and the defensive footwork movement test (T3). The Hexagonal Agility Test primarily evaluates students' rapid reaction ability and footwork transition ability, while the T-Shaped Run Test primarily evaluates students' directional change ability. These three tests are all important factors influencing students' footwork agility. The Defensive Footwork Movement Test primarily evaluates students' ability to quickly perform specialized footwork movements such as sliding steps and retreating steps, providing an evaluation of students' footwork agility from a specialized badminton perspective.

IV. B. Experimental Results

IV. B. 1) Statistics and Comparison of Pre-test Results

Prior to the experiment, students were assessed using pre-selected badminton footwork flexibility evaluation metrics, namely: the hexagonal agility test, defensive footwork movement test, and T-shaped run test. Based on the measured data, a comparison was conducted between the two classes, with the results shown in Figure 10. It can be seen that the mean scores of the two classes in the Hexagonal Agility Test, T-Shape Run Test, and Defensive Footwork Movement Test were comparable, and when an independent t-test was conducted between the two classes based on these results, no significant differences were found (P > 0.05). It can be concluded that the two classes had comparable rapid reaction ability, step transition ability, directional change ability, and ability to quickly execute badminton-specific footwork during the footwork process before the experiment. The students' foundational badminton footwork flexibility was equivalent.

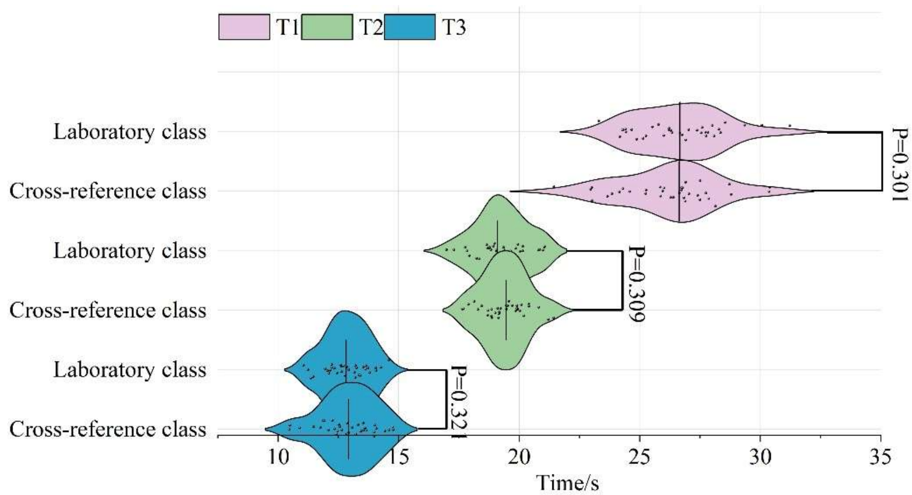


Figure 10: The statistics of the previous results

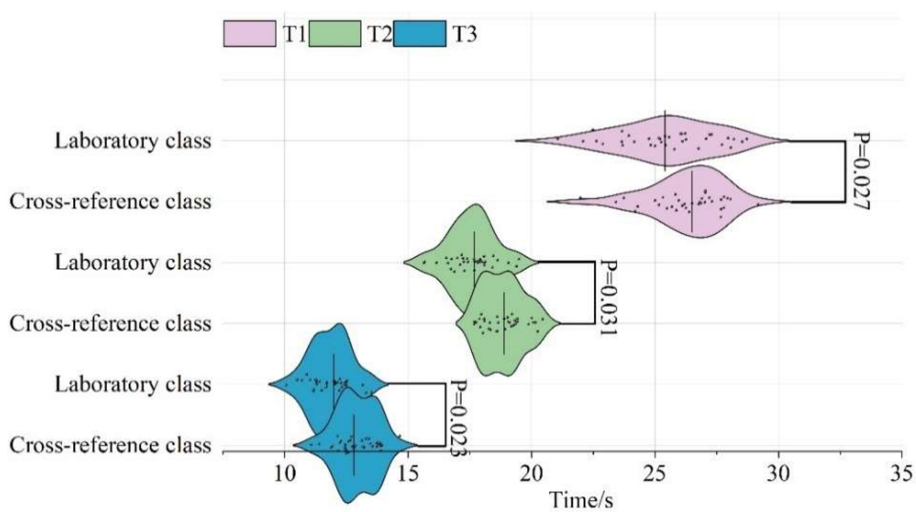


Figure 11: The statistics of the subsequent results

IV. B. 2) Statistics and Comparison of Post-Test Results

The results of the post-experiment assessment and comparison of badminton footwork flexibility between the two classes are shown in Figure 11. It can be observed that:

(1) The mean values of all badminton footwork flexibility assessment data for students in both classes have improved compared to pre-experiment levels, indicating that after 14 weeks of badminton instruction, students' badminton footwork flexibility has improved.

(2) Compared to the control class, the experimental class showed a greater improvement in all indicators, with more ideal test results. Furthermore, when comparing the post-experiment test results of the two classes for various badminton footwork

flexibility assessment indicators, significant differences ($P < 0.05$) were observed between the two classes in terms of hexagonal agility test scores, T-run test scores, and defensive footwork movement test scores. The experimental class's test scores were significantly superior to those of the control class.

It can be concluded that badminton core strength training embedded with deep learning algorithms has facilitated better development of students' badminton footwork flexibility. The application of the motion recognition system has provided greater assistance in improving students' badminton footwork flexibility compared to conventional core strength training conducted in previous badminton instruction

V. Conclusion

This study investigates user motion recognition using KinectV2 and evaluates badminton core strength training movements using a motion evaluation formula defined by the DTW distance of joint angles as a parameter. The total motion evaluation score based on the DTW algorithm was 86.1 points, differing by only 0.5 points from professional scoring, indicating that the method proposed in this paper can effectively assess core strength training movements.

Two classes of students from School A were used as experimental samples. The control class underwent core strength training, while the experimental class used the motion recognition system designed in this paper to assist with core strength training. The results showed that after the experiment, there were significant differences ($P < 0.05$) between the two classes in the hexagonal agility test scores, T-run test scores, and defensive footwork movement test scores. The motion recognition system designed in this paper, when applied to badminton core strength training, had a good effect on improving athletes' footwork agility.

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