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Article

Biomechanical research based on the recognition and detection of the strength of table tennis hitting action

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Abstract: The reason why China's table tennis can continue to this day is because it is an important heritage sports event in the country. In order to ensure the high-level performance of the Chinese table tennis team in the game, the identification and detection of its sports characteristics is a very meaningful work. With the development of computer technology, the use of multimedia intelligence technology to conduct research on competitive tactics has become a general consensus in the sports world. This paper explores the recognition and detection technology of the strength of table tennis hitting movements from the perspective of biomechanics, aiming to provide scientific basis and technical support for improving the performance of athletes. Based on the principles of biomechanics and combined with multimedia intelligent algorithms, this study developed a spatiotemporal graph convolutional network (STGCN) and a motion detection method based on Kinect technology to identify and quantify the hitting strength of table tennis players. The experimental results of this paper show that in the recognition of different types of movements based on the STGCN method, the correct recognition rate of 100 groups of movement strength is 84%, and the correct recognition rate of 500 groups of movement strength is 91.6%; in the recognition of different types of movement strength based on Kinect, the correct recognition rate of 100 groups of movement strength is 97%, and the correct recognition rate of 500 groups of movement strength is 99.6%; it can be seen that no matter how many groups of hitting movements are made, the correct recognition rate of strength based on Kinect is higher than that of STGCN.

Keywords: biomechanics; force recognition; motion detection; multimedia intelligent algorithm; STGCN; kinect technology

1. Introduction

Competitive sports occupy a pivotal position in the world. Sports, with the core of striving for progress and stimulating individual potential, has huge application value in various fields. Table tennis is an important sport in China. As a banner of Chinese sports, Chinese table tennis has always been at the top level in the world after reaching the peak of the world table tennis competition. There are many reasons for the success of Chinese table tennis. In addition to the athlete's own hard training, there are also excellent means of tactical analysis. Tactical analysis refers to the use of different skills reasonably and meaningfully to learn from each other's strengths by analyzing the opponent's grip, stance, and hitting habits according to their own characteristics.

Table tennis has a special historical position in China, and table tennis is always outstanding in Chinese competitive sports. This is not only because of the hard work and talent of the athletes themselves, but also because they have a set of scientific training methods. In the traditional tactical analysis, the coach usually classifies the batting action according to the subjective judgment. This method consumes a lot of time and energy of the coach, so there must be an intelligent method that can help the coach to classify and identify. Although researchers have achieved good results in behavior recognition, there is a big difference between table tennis technical movements and traditional movement classification, and it is necessary to comprehensively consider the complexity of the venue and additional movements. For this reason, it is necessary to carry out more efficient action recognition for table tennis technical actions. The innovation of this paper is that it proposes an action recognition method based on STGCN and Kinect technology based on multimedia intelligent algorithm to recognize the hitting action of table tennis, so as to improve the hitting quality of players.

2. Related work

Table tennis is a confrontational sport that focuses on fast movements and frequent shifting. In general, emotions can affect a person's ability to play table tennis. However, little is known about how emotions affect different aspects of table tennis performance [1]. Although deep learning technology based on multimedia intelligent algorithms is a promising method for identifying human activities, Zhu X designed a low-cost portable device as a coaching assistance system to support table tennis practice [2]. Lv T studied the optimization of athletes' table tennis hitting movements based on image recognition technology [3]. In order to better understand the opponent, Ji Y et al. proposed a vision-based table tennis robot to evaluate the opponent's hitting point. The hitting point information includes the racket posture during hitting and the changes in the ball's motion state before and after hitting, which is the key to judging the opponent's hitting behavior [4]. The researchers found that the hitting action of table tennis is not only the most basic, but also the most important action, and action recognition can be used to evaluate the correctness of the action and improve the effectiveness of table tennis teaching. Because action recognition is of great significance to human-computer interaction technology, it has always been the focus of research on table tennis hitting action recognition. Hu Q used a variety of technologies to study college students to investigate the development of table tennis in colleges and universities in the era of multimedia intelligence. The analysis showed that the atmosphere of social sports is inseparable from the evolution of table tennis technology.

Due to multimedia intelligent algorithms, table tennis is being developed in colleges and universities [5]. In the scientific research of table tennis, the application of multimedia intelligent algorithms is becoming more and more widespread. These algorithms provide new perspectives for the analysis of athletes' movements and the improvement of their skills by analyzing video data, sensor information and biomechanical parameters. In particular, multimedia intelligent algorithms have shown great potential in the identification of batting force. Wang et al. [6] used video analysis technology to identify and quantify the batting force of table tennis players. By analyzing the speed and angle of the racket at the moment of hitting the ball, combined with the flight trajectory and speed of the ball, the batting force can be inferred. This method can not only provide qualitative feedback, but also give quantitative data to help athletes and coaches better understand the effect of each hit. In addition to video analysis technology, wearable devices and sensors are also hot topics in current research. Rigozzi et al. [7] studied the application of wearable devices in the analysis of player motion in racket sports. These devices can directly measure the motion data of various parts of the athlete's body, including joint angles, muscle activity and force output when hitting the ball. By integrating this data, intelligent algorithms can more accurately evaluate the batting force and provide personalized training suggestions for athletes. In addition, with the development of machine learning and deep learning technologies, some research teams have begun to try to use these advanced technologies to improve the accuracy and efficiency of batting force recognition. Li et al. [8] trained models to recognize different batting actions and force patterns. These algorithms can automatically learn and extract features from large amounts of data, thereby achieving more accurate action recognition.

This study developed a new action recognition method combining STGCN and Kinect technology to address the shortcomings of existing research in the quantitative analysis and real-time feedback of table tennis hitting force, improve the accuracy of action recognition, and provide athletes with real-time training optimization suggestions.

3. Motion intensity recognition method based on multimedia intelligent algorithm

Forehand, forehand rub, backhand and backhand rub are the four basic movements of table tennis. Each action rotates the ball in a completely different way, and players can determine the type of rotation in the first place. Therefore, this paper divides the basic actions of table tennis players into 4 categories, as shown in **Figure 1**:

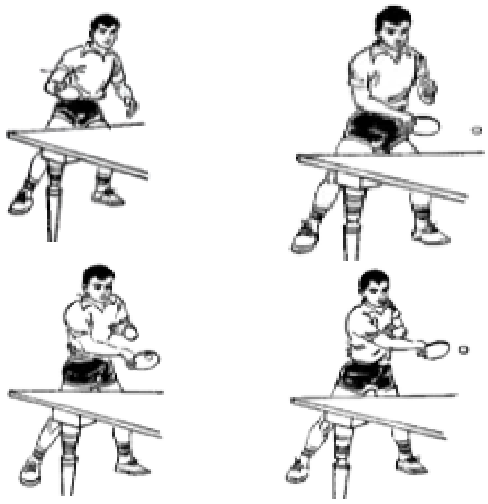


Figure 1. Four basic actions.

As shown in **Figure 1**, table tennis attack has the characteristics of small action and fast speed [9]. When initiating the shot, the body rotates slightly, and the center of gravity is placed on one side of the feet. When hitting the ball, the body is used to drive the arm to rotate, the center of gravity of the body gradually drops, the knees are bent, and the racket is basically parallel to the table. When hitting the ball, people should pay attention to use the wrist to drive the racket, touch the middle and lower end of the ball, and finally adjust their body quickly.

3.1. Batting action and force recognition based on STGCN

The application of computer recognition technology in sports has become very extensive. With the improvement of the technical level of various sports, in order to maintain the high level of movements and seek breakthroughs, people increasingly use computer recognition technology to analyze the competition and training videos of players [10,11]. Computer recognition technology is to use some methods in the image to process the image, so that the tactical analyst can quickly identify some useful tactical information from the image. Due to the sharp increase in the amount of video that needs to be analyzed, manual processing alone is time-consuming and labor-intensive, and the accuracy would also decrease. Therefore, the use of multimedia intelligent technology to effectively and accurately identify table tennis is a hot topic at present [12]. This paper uses CNN to process high-speed videos and automatically identify the strength of table tennis hitting movements. CNN automatically learns to extract features from input images and uses them to train the model to identify the force level when hitting the ball. The features extracted by CNN are then combined with spatiotemporal data to conduct a comprehensive analysis and evaluate the performance of athletes through a multimedia intelligent algorithm framework.

The emergence of graph convolution has further developed the research on motion recognition. Graph convolution is to construct a graph topology when inputting data, and then use the convolution operation to process the data. The use of graph convolution technology in motion recognition can well understand the spatial positional relationship of skeletal joint points, so as to realize the classification and recognition of motion [13]. In order to better understand graph convolution, people must first start with traditional convolution. The traditional convolution structure is shown in **Figure 2**:

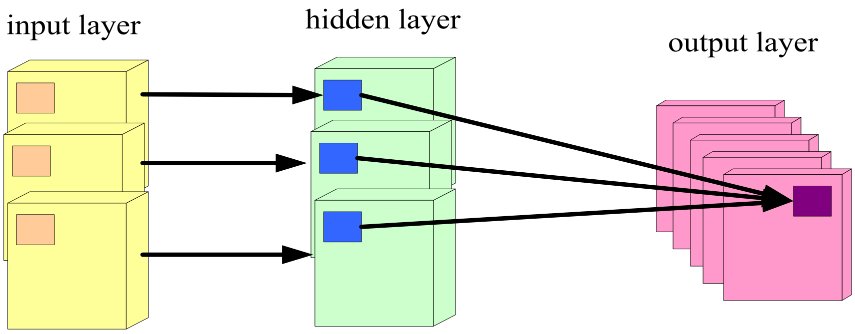


Figure 2. Traditional convolutional structure.

As shown in **Figure 2**, since the image is composed of a large number of regularly arranged pixels, the image is often stored in the computer, and its structure has certain regularity. The convolution operation on the image is actually sliding on the image through the convolution core, and the pixel on the image and the value of the convolution kernel are dot-produced to complete the sliding of the entire image [14].

However, in the bone data, the joint points and the image points in the image data cannot be exactly the same and are not regular, and belong to the non-Euclidean structure [15]. Like the skeleton head joints, the corresponding topological graphs are established with points and edges, which are usually called graph structures. Since the data is composed of graphs, its structural stability cannot be guaranteed when performing traditional convolution operations, so it cannot be processed by conventional convolution methods. Therefore, the spatial characteristics of the graph structure should be obtained by analyzing the graph convolution. The graph convolution is shown in **Figure 3**:

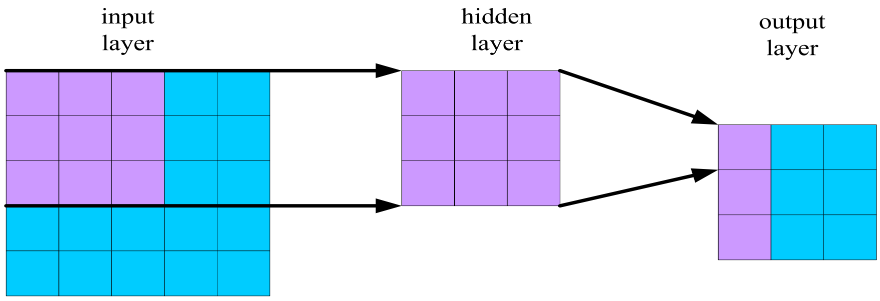


Figure 3. Graph convolution.

As shown in **Figure 3**, the core content of graph convolution is to measure the relationship between nodes by the adjacent matrix and the degree matrix, that is, to gather the information of each node together to form a new node. The corresponding adjacency and degree matrices are given [16].

The degree matrix has only one value on the diagonal, and the adjacency matrix has a value of 0 only when two nodes with edges are connected. The Laplacian matrix is obtained from the degree matrix and the adjacent matrix. The Laplacian matrix can well reflect the relationship between nodes. Its calculation formula is as Equation (1):

$$F = D^{-\frac{1}{2}} A D^{-\frac{1}{2}} \tag{1}$$

Among them, $-\frac{1}{2}$ represents the adjacency matrix. Similar to the traditional convolution method, its calculation is also a process of first sampling and then weighted summation. The sampling method of graph convolution is similar to the traditional convolution sampling method. After the traditional convolution sampling point and its surrounding pixel points, it is input into the convolutional network, while the graph convolution samples the central and surrounding nodes, and then input it into the network [17,18].

In traditional convolution, all parameters are calculated by back-propagation, and after adding the Laplacian matrix, back-propagation and training can be performed. For arbitrary structures, after knowing the initial characteristics of the nodes, the graph convolution method can be used to aggregate, and the result is as shown in Equation (2):

$$F = D^{-\frac{1}{2}} A D^{-\frac{1}{2}} A \tag{2}$$

A represents the trainable network parameters and the feature data found in each node of the input graph structure, in order to better understand the relationship between nodes. Graph convolution would continuously collect edge information and node information.

Considering the skeletal structure of the human body as composed of the connections between joints and bones, some scholars have proposed a graph structure model with joints as nodes and skeletons as edges [19]. On this basis, a graph convolutional network is used to process the spatial structure of nodes, and a temporal convolution is used to process the temporal dimension, resulting in higher-level feature maps. Finally, the corresponding classification is completed through the SoftMax classifier, as shown in **Figure 4**:

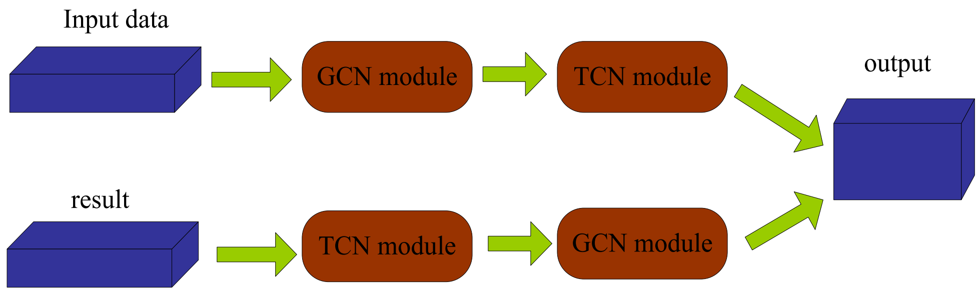


Figure 4. The structure of STGCN action recognition.

As shown in **Figure 4**, in the connection structure of human joint points in a single frame, the adjacent points are sampled, and only the first adjacent node is selected. In each sample, each sample needs to sample *N* joint points. For those that do not meet this requirement, it can be processed by an empty node, and a single node in a single frame of video is aggregated by graph convolution, and its output can be expressed by Equation (3):

$$F_{vti} = \sum_{j=1}^{N} D_{vti}^{-\frac{1}{2}} A_{vti} D_{vtj}^{-\frac{1}{2}} A_{vtj} \omega \tag{3}$$

A_{vti} represents the adjacency matrix, $D_{vti}^{-\frac{1}{2}}$ represents the adjacency information contained in the adjacent points of the joint point, and $D_{vtj}^{-\frac{1}{2}}$represents the identity matrix. The dimension of the identity matrix is the same as the degree matrix of the sampling graph structure with the joint point as the center node, and ωrepresents the physical parameter. It consists of a central joint point, and the feature information contained in other surrounding joint points is aggregated to the central joint point to generate richer feature information, and the rich information is beneficial to the subsequent classification.

After completing the calibration of the internal and external parameters of the camera of the external vision system, according to the geometric model of the camera, after obtaining the image coordinates of any target point in the three-dimensional space, the position (a_d, b_d) in the world coordinate system of the table tennis can be reconstructed to realize its three-dimensional positioning. Assuming that the obtained homogeneous coordinate of the center of the table tennis target in the image coordinate system isA_p, Equation (4) can be obtained:

$$(a_d, b_d, 1)^T = k^{-1} A_p \tag{4}$$

In the calculation process, a_d is used as the initial value of the calculation, and the values of a_d and b_d are close to each other, and the result of convergence can be obtained quickly. After obtaining the numerical solution of A_p, the external parameter matrix of the camera obtained by calibration is set to (R, t), as shown in Equation (5):

$$sA_n = (R, t)A_w \tag{5}$$

Among them, A_w is the normalization coefficient. If:

$$(R, t) = \begin{pmatrix} m_1^T \\ m_2^T \\ m_3^T \end{pmatrix} \tag{6}$$

then m_i^T represents the *i*-th row of (R, t), and the following formula of vector product can be obtained, as shown in Equation (7):

$$\begin{cases} (m_1 - a_n m_3) \bullet A_w = 0 \\ (m_2 - b_n m_3) \bullet A_w = 0 \end{cases} \tag{7}$$

Equation (7) expresses the relationship between the homogeneous coordinate A_p on the normalized image plane and the world coordinate A_w of the target point. When the number of cameras is m_1, this formula can be used to calculate. Using the linear least squares method to solve the formula system, the optimal three-dimensional coordinates of the table tennis ball in the world coordinate system in the least square sense can be obtained, and the three-dimensional reconstruction of the center of the table tennis target can be completed to realize the three-dimensional positioning of the table tennis target.

High-precision sensors are used to capture the changes in force and acceleration when athletes hit the ball. These key data are quantified and form the basic input of the recognition model. The STGCN model is used to combine these force features with the spatiotemporal features of the action to generate a comprehensive feature vector, which not only deepens the understanding of the action characteristics, but also greatly improves the accuracy of force recognition. The model network structure and parameters are optimized to enhance its sensitivity to force changes, and regularization technology is used to effectively avoid overfitting problems and ensure the robustness of the model. Integrating this technology into the real-time feedback system provides athletes with instant force feedback, helping them monitor and adjust their hitting force in real time during training and competition.

3.2. Table tennis hitting action and force recognition and prediction based on kinect

Pre-judgment is that when the opponent has not yet shot, the opponent's posture and other parts of the body can be used to complete the action of counterattacking them [20]. In the fast movement of table tennis, the flying speed of the ball is very fast, and the trajectory is not fixed, so players need to predict the ball according to the actions of the opponent, so as to make corresponding responses and improve the success rate of the game.

A large number of studies have shown that in the fast ball game, high-level players must judge the opponent's incoming ball through the opponent's actions. In table tennis, this step is the most difficult and the most critical one. Athletes should judge the direction and intensity of their rotation by judging the opponent's batting action, so as to provide more time for judging the opponent's ball-returning action. Based on the Kinect depth camera, this paper acquires the characteristics of athletes' straight-shooting movements by collecting human skeleton data, and presents an effective action recognition algorithm.

Kinect can extract many key points from the human body, but for table tennis players, the basis of its prediction is the straight shot. For the convenience of research, it is assumed that all straight shots are done with the right hand, the extracted motion feature sequences are composed of data of right joint points, and M_i is the extracted three-dimensional data, and Equation (8) is obtained:

$$M_i = [a_i, b_i, z_i] \tag{8}$$

Kinect can be used to obtain the 3D coordinate data of the right joint. If the annotation is F, there is Equation (9):

$$F = \{M_1, M_2, \ldots, M_n\} \tag{9}$$

Among them, n represents the number of frames required to complete an action.

Motion analysis can be used with Kinect to identify the type of motion. Dynamic Time Warping (DTW) algorithms can be used to identify the speed of motion, and it is crucial to find the time series of each complete action before classifying the activity.

In the case of not serving the ball, the movement of the player's hand holding the clap is relatively stable and does not produce a great acceleration, but it would produce a great acceleration in the process of hitting the ball. There must be three consecutive coordinates in the calculation, and the acceleration data is calculated by a series of data in the movement of each step. Continuous image data is recorded as Equation (10):

$$H = [a(i-1), b(i-1), z(i-1)] \tag{10}$$

It is easy to know from the acceleration calculation formula:

$$a_x(i) = \frac{[a(i-1), b(i-1), z(i-1)]}{\Delta t^2} \tag{11}$$

The time interval between every two frames of images isΔt.

A three-dimensional description of the change in the acceleration value of an action illustrates how the acceleration value would change significantly at the beginning and end of the hitting action, as shown in **Figure 5**:

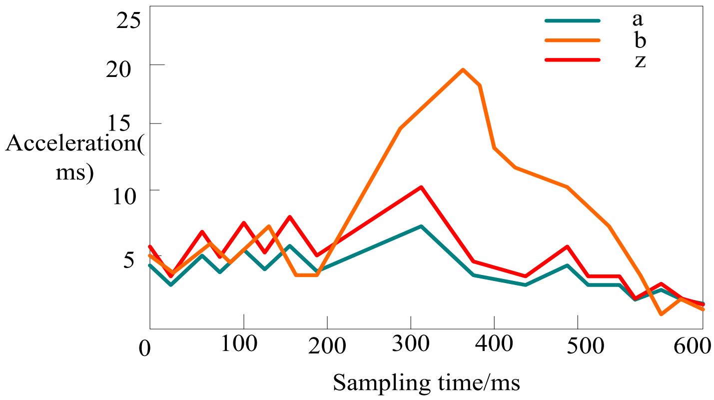


Figure 5. Three-dimensional acceleration numerical change diagram.

As shown in **Figure 5**, $A(i+m)$ is the three-dimensional acceleration data recorded in the depth image of the *i*-th frame. The Euclidean distance is determined by calculating the difference between acceleration data in successive image frames and comparing it to a threshold *T*:

$$\|A(i+m) - A(i)\| \geq T \tag{12}$$

Then it can be determined that the data of the *i*-th frame image is the starting point of the action. If:

$$\|A(i+m) - A(i)\| \prec T \tag{13}$$

Then the data of the *i*-th screen can be determined as the end point of the operation, where *m* = 1, 2, 3, 4, 5. In fact, the screen can display the change of acceleration at the same time, but there may be some errors, such as the player's body would move due to habit. In the formal swing, the athlete's movement would appear a continuous acceleration, and the acceleration process is limited.

The origin of the coordinate system selected by the camera is usually inconsistent with the center of the ellipse formed by the fairway, so the measured coordinates must be converted into coordinates with the ellipse as the origin, and then the next step is performed. Assuming that the image coordinate system is $\frac{a}{b}$, the ellipse coordinate system is substituted into the image coordinate system, and Equation (14) is obtained:

$$\begin{bmatrix} a_t \\ b_t \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & \frac{b}{a} \end{bmatrix} \begin{bmatrix} a_{tt} \\ b_{tt} \end{bmatrix} \tag{14}$$

The coordinate of any point on the ellipse is (a_t, b_t), and the coordinate of the corresponding point on the circle is (a_{tt}, b_{tt}).

When hitting the ball, the action speed determines the rotation of the ball. When the speed of the same movement changes, the characteristic sequence curves of the action are comparable. In this paper, DTW is used to classify and identify the speed of impact action. The DTW path search is shown in **Figure 6**:

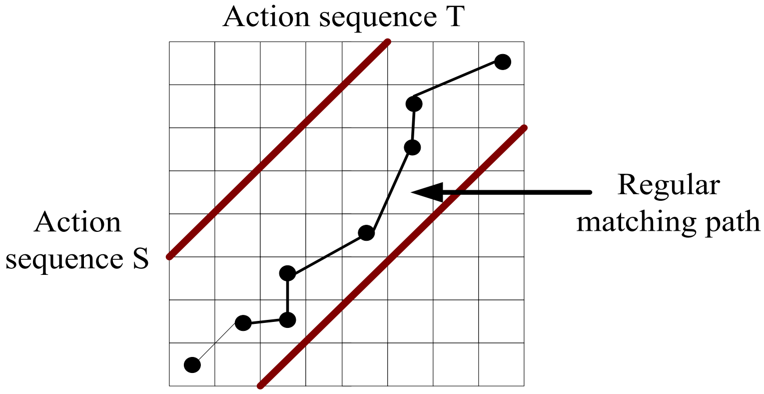


Figure 6. DTW path search.

As shown in **Figure 6**, the DTW algorithm can determine the degree of similarity between two sequences. It uses Euclidean distance to represent similarity. However, the relationship between the two sequences, that is, the points, must be re-planned to find the matching path with the shortest distance. Assuming templates and test order as in Equations (15) and (16):

$$T = (T_1, T_2, \ldots, T_n) \tag{15}$$

$$S = (S_1, S_2, \ldots, S_m) \tag{16}$$

Among them, *n* and *m* represent the lengths of the two sequences.

The cumulative distance is defined as the product of the current grid point distance$d(T_i, S_j)$ and the cumulative distance of the lowest adjacent element that can reach the point$D(i,j)$, which is Equation (17):

$$(i,j) = d(T_i, S_j) + min\begin{Bmatrix} D(i,j-1) \\ D(i-1,j) \\ D(i-1,j-1) \end{Bmatrix} \tag{17}$$

The similarity between two samples is represented by the size of the cumulative distance, the best path is created by the set of all points, and$D(i,j)$is the shortest total distance between *T* and *S*. When the value of $D(i,j)$ is low, the two sequences are more similar to each other, and when the value of $D(i,j)$ is high, the difference between the two sequences becomes larger.

The DTW algorithm can be used to determine how similar two actions are to each other and how similar $S_1$and S_2 are, and then the class of the action sequence with the highest similarity is L, and the test action sequence is T, as shown in Equation (18):

$$L(T) = L(S_i), i = \begin{cases} 1, D(T, S_1) \prec D(T, S_2) \\ 2, D(T, S_1) \succ D(T, S_2) \end{cases} \tag{18}$$

The action speed types of the test sequence can be divided into fast and slow, and then the strong and weak spin strengths of table tennis can be determined based on the fast and slow motion speeds.

Kinect is used to collect the three-dimensional joint positions and motion trajectories of athletes when hitting the ball. Then, these data are analyzed to extract force features, including joint acceleration and velocity changes, which can quantify the force and speed when hitting the ball. These force features are combined with spatiotemporal features to form a comprehensive feature set. In order to improve the accuracy of recognition, the existing action recognition algorithm is optimized to enable it to capture force changes more sensitively, and the model is trained through machine learning techniques such as random forest or gradient boosting machine to enhance the classification ability of hitting actions with different force levels. In addition, a real-time analysis module is developed to instantly feedback the recognition results to the athletes. Finally, the force recognition technology is integrated into the Kinect-based action recognition system.

4. Experimental comparative evaluation of different table tennis hitting action recognition methods

This study used high frame rate videos as input data, and identified and quantified the hitting force of table tennis players through a series of processing steps including preprocessing, joint point extraction, action segmentation, feature extraction, and STGCN application. Key parameters such as learning rate, number of hidden layer units, and feature extraction window were carefully set to optimize model performance. The graph convolution operation was based on the aggregation and update of node features, while the model training adopted the cross entropy loss function and Adam optimizer. The effectiveness of the algorithm was verified by the accuracy rate. Adult table tennis players with at least 1 year of training experience were selected as participants in this study. Data were collected using a calibrated Kinect sensor to ensure accuracy. The experiment included warm-up and standardized action execution, and data preprocessing and analysis were performed using a unified method to reduce bias.

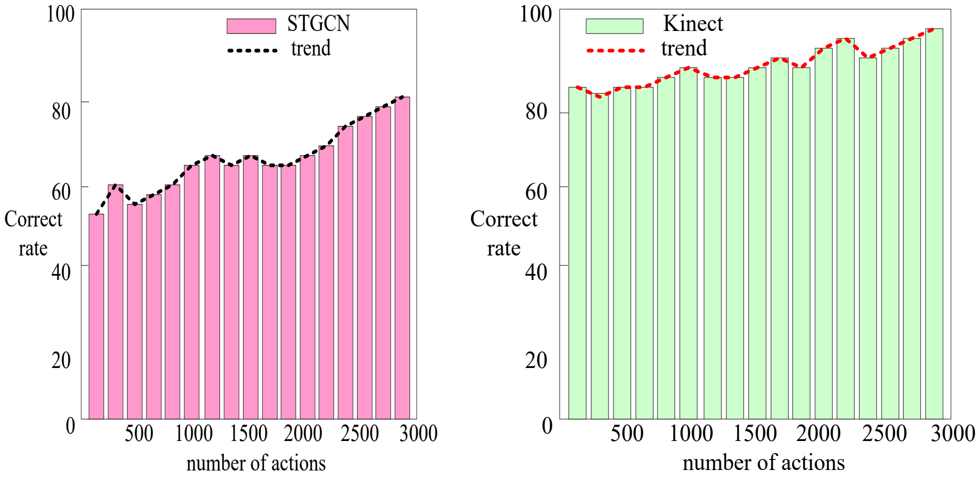
The experimental environment of this paper is the Windows7 platform with 2GB memory. When the data set I is collected, the players are simulated when they are close to the table tennis table. This dataset has a total of 5000 video actions with a frame rate of 25 frames per second. In this paper, 2000 video actions are used as training set, and the remaining 3000 video actions are used for experiments.

When the dataset II was collected, the contestants performed simulations far away from the table. A total of 3500 videos were collected in this paper, of which 2000 were training sets and 1500 were test sets.

4.1. Recognition accuracy of the two recognition methods in different datasets

In order to test the correctness of the STGCN and Kinect recognition methods proposed in this paper in the action recognition of table tennis technology, firstly, 3000 video actions in the motion dataset I are used as experimental data. The recognition accuracy of STGCN and Kinect recognition methods is shown in **Figure 7**.

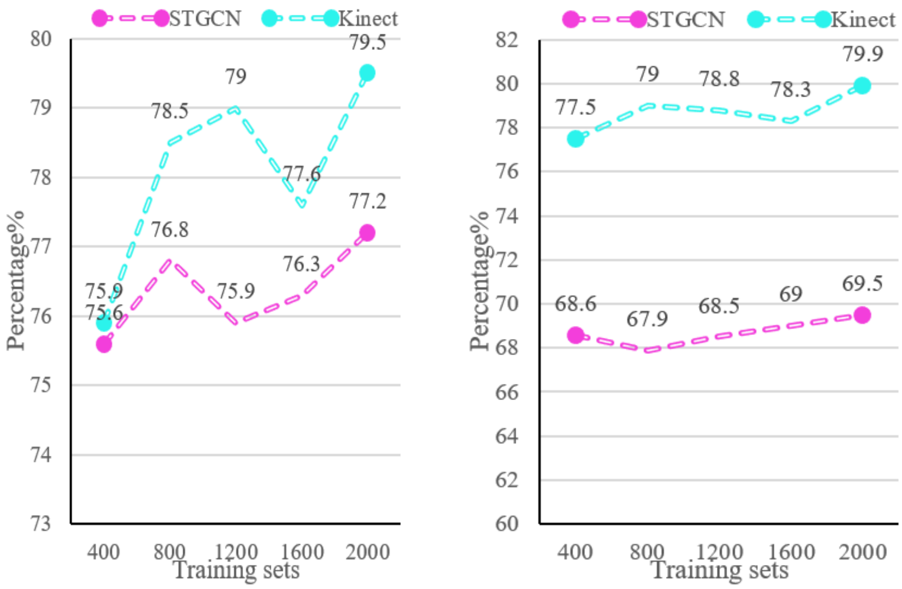
As shown in **Figure 7**, through the analysis of **Figure 7a**, the results show that although the correct rate of the STGCN recognition method is gradually increasing, the increase is very small. Through the analysis of **Figure 7b**, it can be seen that although the accuracy rate of the Kinect recognition method has not increased significantly, with the increase of experimental data, the accuracy rate has remained above 80%.



(a) **(b)**

Figure 7. Comparison of recognition accuracy between STGCN and Kinect recognition methods. **(a)** Correct rate of STGCN recognition method; **(b)** Correct rate of Kinect recognition method.

In addition to using STGCN for recognition, the use of Kinect for action recognition is also a hot topic in this field. For this reason, STGCN and Kinect are used for comparison in the experiment. First, the results obtained by data processing are used, that is, the two-dimensional plane coordinate and three-dimensional coordinate data are used as input. The 2000 training sets of data set II are trained and compared the recognition accuracy of the two methods in two-dimensional plane coordinates and three-dimensional coordinates, as shown in **Figure 8**:



(a) **(b)**

Figure 8. The recognition rate of two recognition methods in 2D coordinates and 3D coordinates. **(a)** The recognition rate of the two recognition methods in 2D coordinates; **(b)** The recognition rate of the two recognition methods in 3D coordinates.

As shown in **Figure 8**, **Figure 8a** can be found in the two-dimensional coordinates, the lowest recognition rate of Kinect recognition method is 75.9%, and the highest is 79.5%; the lowest recognition rate of STGCN recognition method is 75.6%, and the highest is 77.2% %. It can be seen that the recognition rate of the Kinect recognition method is higher than that of the STGCN recognition method. **Figure 8b** can be found in the three-dimensional coordinates, the lowest recognition rate of the Kinect recognition method is 77.5%, and the highest is 79.9%; the lowest recognition rate of the STGCN recognition method is 67.9%, and the highest is 69.5%. It can be seen that even in the three-dimensional coordinates, the recognition rate of the Kinect recognition method is higher than that of the STGCN recognition method, and the recognition rate of the Kinect recognition method is not much different from that in the two-dimensional coordinates. However, the recognition rate of STGCN recognition method in three-dimensional coordinates is significantly lower than that in two-dimensional coordinates.

This shows that in table tennis technology, it is better to use Kinect to identify coordinate information than to use STGCN to identify coordinate information. The reason for this phenomenon may be due to the differences in the habits of players when playing, which would lead to more movements, but these movements cannot determine which type of sports is currently. However, in the actual network training, the relevant data would have a certain impact on the training and training effect of the network.

4.2. Recognition accuracy of the two recognition methods under different occlusion conditions

Occlusion is a common problem in batting action recognition of table tennis. In order to prevent the experimental error caused by the occlusion problem, and the added actions in the table tennis game would have an impact on the final discrimination results, dataset II is used to compare the recognition accuracy of the two methods with and without occlusion, as shown in **Figure 9**:

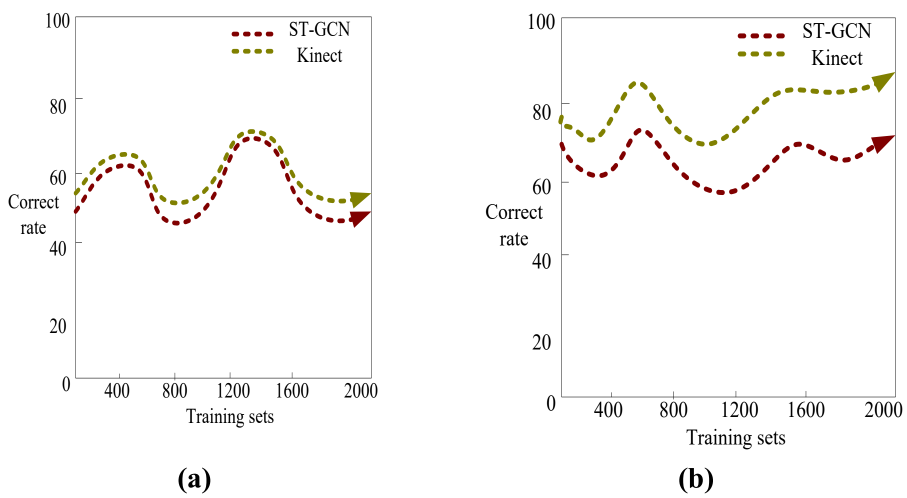


Figure 9. Comparison of the accuracy of the two methods with and without occlusion. **(a)** The accuracy of the two methods in the case of occlusion; **(b)** The accuracy of the two methods in the case of no occlusion.

As shown in **Figure 9**, **Figure 9a** shows that the difference in the accuracy of the two methods is not very large in the case of occlusion. However, it can still be seen that the accuracy rate of Kinect recognition is slightly higher than that of STGCN recognition. **Figure 9b** shows that in the case of no occlusion, the difference between the accuracy rates of the two methods gradually widens, and the accuracy rate of Kinect recognition is much higher than that of STGCN.

The above comparative test results show that under the condition of not being disturbed by obstacles, using Kinect as the recognition method, its effect is better than that of STGCN recognition method.

This paper also collected the data of 5 table tennis players, and performed four different action demonstrations for them, a total of 1000 groups. 500 sets of data were selected for detection, and different types of play rotation were determined according to different types of motion, and the test data was input into the algorithm for training and identification. The force recognition accuracy is shown in **Tables 1** and **2**. A 95% confidence interval was calculated for the recognition accuracy of each action intensity to assess the statistical uncertainty of the accuracy. The confidence interval provides a credible range for the accuracy estimate and reflects the variability of the results that may be obtained by repeating the experiment under similar conditions.

Table 1. Recognition and detection results of different action strengths based on STGCN.

Frequency/action	Forehand	Forehand rub	Backhand	Backhand rub	Correct number	Accuracy	95% Confidence Interval
100	75	2	10	2	84	84%	[82%,86%]
200	130	5	15	13	163	81.5%	[79%,84%]
300	201	7	29	16	253	84.3%	[82%,86%]
400	326	8	17	9	360	90%	[88%,92%]
500	385	11	40	22	458	91.6%	[90%,93%]

Table 2. Kinect-based detection results of different motion strengths.

Frequency/action	Forehand	Forehand rub	Backhand	Backhand rub	Correct number	Accuracy	95% Confidence Interval
100	80	0	15	2	97	97%	[95%, 99%]
200	155	3	20	12	190	95%	[93%, 97%]
300	228	5	35	19	287	95.6%	[94%, 97%]
400	350	9	20	15	394	98.5%	[97%, 99%]
500	408	10	50	30	498	99.6%	[99%,100%]

As shown in **Table 1**, in the recognition results of different action types based on STGCN, when the test data is 100, the correct rate is 84%; when the test data is 200, the correct rate is 81.5%; when the test data is 300, the correct rate is 84.3%; when the test data is 400, the correct rate is 90%; when the test data is 500, the correct rate is 91.6%. It can be seen that the recognition accuracy of the STGCN recognition method first decreases and then increases with the change of the experimental data.

As shown in **Table 2**, in the recognition results of different action types based on Kinect, when the test data is 100, the correct rate is 97%; when the test data is 200, the correct rate is 95%; when the test data is 300, the correct rate is 95.6%; when the test data is 400, the correct rate is 98.5%; when the test data is 500, the correct rate is

99.6%. It can be seen that the recognition accuracy of the Kinect recognition method is much higher than that of the STGCN recognition method, and both are above 90%.

4.3. Measures to improve the quality of table tennis shots

(1) Moderate arc manufacturing

The arc of table tennis refers to the flight path of the ball in mid-air. The flight path of the ball directly affects the hit rate and quality of the serve. After the racket hits the ball, the movement of the ball in the air would be affected by its own gravitational force and airflow, and would present an arc shape. The more the arc bends at a certain height, the greater the chance of a hit. However, if the arc is excessive, it is easy to backfire, so it is necessary to bend properly. When hitting the ball, it is the best state to connect the flight arc of the ball with the flight trajectory of the second arc. The second arc is the line connecting the air flight trajectory when the ball bounces from the opponent's table to the opponent hitting the ball with the racket or landing.

(2) Improvement of fast attack speed

Speed plays a very important role in table tennis. The traditional Chinese style of play is close-to-table fast break, which is to highlight the word "fast". Speed plays a pivotal role in table tennis to win fast and create chances to hit the ball. The speed of table tennis has its own characteristics, which consists of the following two elements. One is the forward speed of the ball, that is, the speed of the ball in mid-air after the racket hits the ball. Second, after the ball hits the ground, in the next rebound time, a shorter rebound time is beneficial to increase the speed of the ball.

In order to improve the mastery of the landing point, people should pay attention to the use of flexible walking in training and competition, and determine their own position according to the path and landing point of the incoming ball. The direction of the shot, the strength of the shot, the time of the shot, the size of the shot arc, the trajectory of the shot, and the shape of the shot all affect the final score. In order to master the trajectory and placement of the ball, it is necessary to strengthen the technique of the hand and improve the control of the ball by the fingers and wrist.

5. Conclusions

This paper studies a method for identifying the force of table tennis shots that combines biomechanics and multimedia intelligent algorithms. The accuracy of action recognition is improved by using STGCN and Kinect technology. Experiments show that the system is efficient and practical in action recognition and force analysis, providing scientific technical support for table tennis training and competition. However, the research has limitations such as sample restrictions and controllability of the experimental environment. Future research needs to expand sample diversity, enhance the reality of the experimental environment, optimize the algorithm to meet real-time processing requirements, and explore the application potential of this technology in other sports.

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