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Article

Biomechanical analysis of pace adjustment in table tennis players combined with image recognition technology

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Abstract: In this paper, we first preprocess the sample images of table tennis player's pace, and under the theory of sports biomechanics, we propose to use the IDTW algorithm (Improved Dynamic Time Warping Algorithm) to extract the features in the sample images, which mainly contain biomechanical parameters such as acceleration and angular velocity. By describing the basic pace of table tennis technology, the image segmentation principle in image recognition technology is utilized to construct the controlled pace reduction algorithm. Combining the actual sports image recognition and biomechanical analysis, we explore the pace adjustment of table tennis players supported by intelligent technology. The IDTW algorithm has a better accuracy in recognizing the pace of table tennis players, and its overall recognition accuracy is 92.00%. The value of acceleration change in the swing and follow-through phase is 1.1 m/s^2, while the value of acceleration change in this phase is only 0.069 m/s^2 for beginner table tennis players, which indicates that the beginner players do not control the power in the process of pacing action, resulting in the acceleration change of the right hip point in the Y-direction of the lead-in phase and swinging and follow-through phases is too small. This study provides a theoretical guidance value for the intelligent development of table tennis pace movement adjustment.

Keywords: IDTW; biomechanics; image recognition technology; pace adjustment

1. Introduction

Rapid, accurate and variable table tennis footwork is an important factor that affects the effectiveness of athletes' striking movements and determines the outcome of the game. The quantitative analysis of pacing in table tennis with the help of sports biomechanics methods and tools can provide theoretical guidance for the optimization of athletes' movement skills and the prevention of injuries [1–4]. In table tennis, athletes need to move and turn frequently, so the design of gait and posture is crucial to their performance [5].

With the development of science and technology, image recognition technology has become a very important technology in recent years, which can be applied to various aspects. One of the important areas is motion monitoring. Intelligent image recognition technology can assist people to perform various sports, and monitor and analyze people's sports status in real time [6,7]. Table tennis, as a highly technical and tactical sport, has also gradually introduced image recognition technology, which is used in the automatic acquisition system of technique and tactics. The automatic acquisition system of table tennis technique and tactics is a kind of system realized by image recognition technology, which is able to collect, analyze and record all kinds of technical and tactical data in table tennis games in real time [8–11]. This kind of system can utilize high-speed camera to capture the game screen, and accurately identify and measure the position of the paddle, the trajectory of the ball, the rotation of the ball, etc. through image recognition technology. By analyzing and counting these data, detailed technical and tactical guidance can be provided to players and coaches to help them improve and enhance their game [12–15].

Different from existing research, this paper optimizes the path extraction and processing of table tennis athletes, and analyzes the characteristics of athletes in a more effective way. The image information is read from the BMP (Bitmap-File) file using a computer device, and then the read image information is preprocessed (median filtering, image grayscaling, image binarization, etc.), and features, such as acceleration, angular velocity, etc., are extracted from the motion trajectory of the table tennis player's stride based on the improved DTW (Dynamic Time Warping) algorithm, and the different features are fused to obtain a more comprehensive description of the table tennis player's stride features. These features are used as inputs for recognition processing by a trained classifier (SVM) to determine the category of table tennis player's pace. Comprehensive image recognition technology and biomechanics theory are used to establish the spatial right-angle coordinate system of x, y, z, and the controlled pace reduction algorithm is constructed to realize the intelligent adjustment of table tennis player's pace. An experimental scheme is adopted to evaluate and analyze the pace adjustment of table tennis players with intelligent technology support.

2. Research on pace adjustment of table tennis players supported by intelligent technology

2.1. Image preprocessing

In this topic, the key techniques of image preprocessing for image recognition technology are image data reading, image grayscaling, acquisition of image gradient, image feature region determination, matching of two images, image binarization, image refinement, image expansion, image de-discrete point operation, region localization of objects, and acquisition of object center point. These are some of the processing methods often used in image processing to provide a theoretical basis for the implementation of subsequent research work.

2.1.1. Image data reading

The first step is to read the image information from a BMP file. Be careful to release useless file handles in time to avoid memory leakage. There are two cases of image data reading, the first case is to read the image when performing background extraction, and the second case is to read the image when performing motion judgment.

2.1.2. Median filtering of images

Median filtering is a noise removal smoothing operation, which involves sorting the number, values of pixels related to the currently processed pixel point and then assigning the intermediate values to the currently processed point [16]. Images are always added some noise during shooting, scanning or transmission, which affects the quality of the image, after median filtering these noises can be removed and smoothing of the image is also achieved. Image smoothing can be achieved by a variety of filtering methods, such as low-pass filtering, Gaussian filtering and so on. It is worth mentioning that the image smoothing achieved by median filtering does not destroy the edge information of the image. This is necessary for the operation of edge extraction to be performed. In this project, a 3 × 3 filter template is used.

2.1.3. Image grayscaling

The process of image grayscaling is the process of converting a color image into a black and white image, which should be converted into a grayscale image frequently because grayscale graphics are easier to perform operations on than color images [17,18]. There is no specific criterion for this conversion, generally it is based on the 3 components of RGB (Red Green Blue) in the original image and their weights.

2.1.4. Image binarization

Image binarization is the image display when the intelligent see two colors, the principle of image binarization is shown in **Figure 1**. There are many methods of binarization of its body, the more commonly used is the threshold determination method [19]. Given a numerical value, when the brightness value of the pixel in the grayscale image is less than this value, the pixel is set to be black (which can be other colors), and when the brightness value of the pixel in the image is greater than this value, the pixel is set to be white (which can be other colors) Threshold selection has an automatic threshold selection method and a manual threshold selection method.

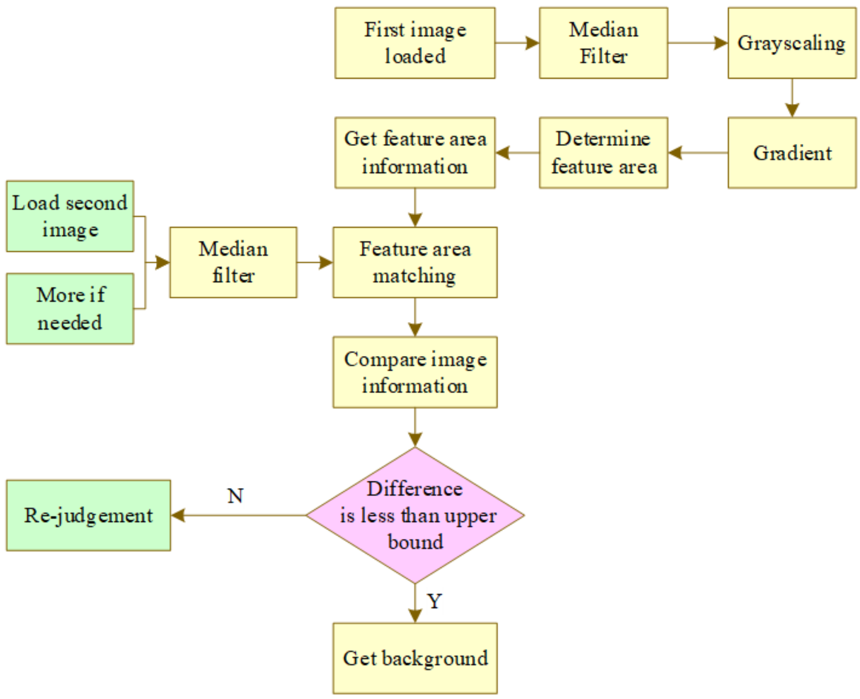


Figure 1. Image binarization principle.

2.1.5. Image expansion

Image expansion is based on the conditions, the image of the current point of the color assigned to the surrounding points, or the surrounding points of the color assigned to the current point, and ultimately make the objects we care about appear more flat, more obvious. The expansion of the image belongs to the graphics content, the specific implementation, according to the need to set the expansion conditions, the system uses a four-direction judgment algorithm, that is, the current point of the top and bottom of the left and right of the current point of the point of a point of color is white, the current point of the color of the fill into black. The result is to make more pixel points, which is convenient for the following operation of boundary extraction.

2.1.6. Image de-discrete points

The resulting contour image will have many discrete black dots. These black dots may be created by noise during the image capture process, or there may be some areas inside the object that have dots with large pixel variations. If these points are not removed, the results of the study will be affected. The number of points used in this project is three, to realize such a de-discrete operation, the programming needs to use recursion to deal with it. Because recursion is inefficient, try not to set the number of points of continuity very high. When determining continuity, an eight-direction recursion is used.

2.2. Image recognition technology

2.2.1. Image segmentation

Image segmentation assigns a predefined category label to each pixel in an image, among them, deep learning semantic segmentation makes full use of the semantic information of the image compared to the traditional image segmentation again, which is the most representative, and the workflow of deep learning based semantic segmentation is given here. Its workflow can be divided into two parts: feature extraction and generation of segmentation results, in the feature extraction part, the input image will be extracted by feature coding to extract high-level semantic features, and in this process, the features may be enhanced by feature selection and then using feature fusion, and then enter the generation of segmentation results part, the obtained feature map will be classified by pixels to get the rough segmentation results map, and means can be taken for processing to optimize the segmentation result. Segmentation of images by image thresholding is the main method used in this research and is the simplest image segmentation method, which is simpler to implement and less computationally intensive. This method is suitable for images where the target and background occupy different gray level ranges. It uses one or more thresholds to divide the gray levels of an image into parts that do not overlap each other and identifies pixels in the same part as belonging to the same object.

2.2.2. Support vector machine based recognition classifier

Support Vector Machines The main idea is to find a hyperplane in space that demarcates all data samples and that has the minimum distance from the hyperplane and the maximum distance from the hyperplane for the sample data points on either side of the hyperplane, both spacing maximization, and differentiating the data as much as possible. While including as many data points as possible, so that all data points are at the minimum distance from that hyperplane, and no loss is counted for the points located in the plane, the loss value is the distance from the plane for the points that are not in the hyperplane. Using the support vector machine as a classifier improves the tolerance of the model, which not only reduces the computation of the model, but also further reduces the computation of the loss value, reduces the time consumption, improves the model response speed, and achieves the task's desired goal as much as possible.

2.3. Theories of exercise biomechanics and measurement of its parameters

2.3.1. Theories of exercise biomechanics

The human movements studied in this paper are based on the daily behavior of the human body and sports, and the purpose of the study of the biomechanical mechanics of sports is precisely to find the basic laws from these movements and to describe them quantitatively in the form of biology, mechanics, mathematics, etc. [20]. Its significance lies in the fact that it can provide valuable information to athletes and their coaches, ergonomists and others. In order to effectively analyze the human body movement, we are required to first have a certain understanding of the common parameters in sports biomechanics, which mainly include: velocity, acceleration, angular velocity, displacement, angular displacement, force, moment, mass, moment of inertia and so on. In this paper, the following parameters are mainly involved:

(1) Acceleration

The ratio of the increment of velocity to the time taken for that increment is called the average acceleration, and instantaneous acceleration is the limiting value of the average acceleration for an infinite hour of time. Acceleration is a vector quantity with the same direction as the direction of velocity and displacement.

(2) Angular velocity

Average angular velocity is the ratio of angular displacement to time over a period of time, and instantaneous angular velocity is the limiting value of average angular velocity for an infinite number of hours. Angular velocity is also a vector quantity, and the direction is the same as the angular displacement.

2.3.2. Feature extraction

After image processing of the samples, features such as acceleration, angular velocity, etc. are extracted from the motion trajectory of the table tennis player's pace based on the improved DTW algorithm, and the different features are fused to obtain a more comprehensive characterization of the table tennis player's pace. These features are used as inputs for the recognition process by a trained classifier (SVM) to determine the category of table tennis player's pace.

In order to obtain the features of each action of table tennis players at different scales, the study introduces singular value decomposition in the two-dimensional DWT algorithm and designs an improved DWT algorithm. The global feature extraction of table tennis batting movements is carried out firstly by setting the training samples as M, $M = X_1, X_2, \cdots, X_M$, and the features of each training sample as N, $X_M = (X_1^M, X_2^M, \cdots, X_N^M)^T$. The samples are downscaled by principal component analysis, which reduces the interactions and interferences between the features, and at the same time removes the correlations between the samples and reduces the redundancy information of the data. The principal component analysis (PCA) is used to reduce the high dimensional data to the low dimensional space, while retaining the main change information in the data. In this study, the extracted step feature vector is the input data of the PCA, which simplifies the complexity of the data through the reduction of the operation, and reveals the potential patterns. The mean and covariance of all samples are calculated as shown in Equation (1):

$$\begin{cases} \hat{X} = \frac{1}{M}\sum_{i=1}^{N} X_i \\ C = \frac{1}{M}\sum_{i=1}^{N}\left(X_i - \tilde{X}\right)\left(X_i - \hat{X}\right)^T \end{cases} \quad i \in M \tag{1}$$

In Equation (1), X represents the mean vector of all training samples and C represents the covariance matrix. Then the eigenvalues and eigenvectors are obtained according to the eigenequation, and the expression of the eigenequation is shown in Equation (2):

$$\begin{cases} |C - \lambda I| = 0 \\ |C - \lambda_i I| u_i = 0 \end{cases} \tag{2}$$

In Equation (2), λ represents the eigenvalue, I represents the unit matrix, and u_i represents the eigenvector of the i-th feature. In the next step, the eigenvalues are arranged in order from the largest to the smallest, and the cumulative contribution rate is calculated, and the eigenvectors with larger contribution rate are used to construct the eigenspace, and the cumulative contribution rate is calculated as shown in Equation (3):

$$\alpha = \frac{\sum_{i=1}^{k} \lambda_j}{\sum_{j=1}^{n} \lambda_j} \tag{3}$$

In Equation (3), α denotes the cumulative contribution rate and k denotes the number of eigenvectors. The resulting samples are then projected into the subspace and the expression is given in Equation (4):

$$Y = U^T X \tag{4}$$

In Equation (4), Y represents the projection coefficients and U represents the feature subspace, and the projection coefficients are used as the global features of the table tennis batting action. Then the local feature extraction of table tennis batting action is carried out, which is calculated by DWT algorithm. The calculation of wavelet transform process of feature image of table tennis player hitting the ball is shown in Equation (5):

$$S = A + \sum_{i=1}^{n}\left(D_w^i + D_L^i + D_d^i\right) \tag{5}$$

In Equation (5), S represents the value after wavelet decomposition, n represents the number of layers of wavelet decomposition, A represents the low-frequency component of the table tennis player's batting feature image after decomposition in the n-th layer, and D_w^i, D_L^i, D_d^i represent the high-frequency components of the image in the horizontal, vertical, and diagonal directions in the process of wavelet transform, respectively. Then the feature subgraphs are further extracted by singular value decomposition, which is calculated as shown in Equation

(6):

$$A = U \sum V^T \tag{6}$$

In Equation (6), A represents the matrix of the eigen subgraph, U denotes an orthogonal matrix of order $M \times M$ obtained by singular value decomposition, Σ denotes a diagonal matrix of order $M \times N$ obtained by decomposition, and $\Sigma = \begin{bmatrix} \Sigma_1 & 0 \\ 0 & 0 \end{bmatrix}$, V^T denote the transpose of the orthogonal matrix of order $N \times N$ obtained by decomposition of the eigen subgraph. Where the expressions for the singular values and their number are shown in Equation (7):

$$\begin{cases} r = rank(A) \\ \Sigma_1 = diag(\sigma_1, \sigma_2, \sigma_1, \cdots, \sigma_2) \end{cases} \tag{7}$$

In Equation (7), r represents the number of singular values, rank denotes the ranking function, diag denotes the diagonal matrix, and σ denotes the singular values. In the next step, the global and local features of the table tennis batting action are combined by the series level fusion method to obtain a fused feature vector, whose expression is shown in Equation (8):

$$V_F = \left[\frac{V_G}{\sigma_1}, \frac{V_L}{\sigma_2} \right]^T \tag{8}$$

In Equation (8), V_F represents the fusion feature vector, V_G represents the global feature vector, and V_L represents the local feature vector. Since the table tennis ball has directional characteristics when the player strikes the ball, it is necessary to establish the mathematical relationship of the table tennis ball movement and construct a bi-objective function by discrete cosine transform, and the function expression is shown in Equation (9):

$$\begin{cases} x = X_1 + r\cos\left(\theta_k + arctan\dfrac{Y_2}{X_2} + \theta_4\right) \\ y = Y_1 + r\cos\left(\theta_k + arctan\dfrac{Y_2}{X_2} + \theta_3\right) \end{cases} \theta_1 \le \theta_k \le \theta_2 \tag{9}$$

The improved DTW algorithm determines the weight coefficient of each skeleton and the size of the two motion sequence distances is calculated according to the mean shift algorithm. This method can be a good way to achieve the body action score, improve the influence of the key node weight, improve the accuracy of the scoring of the table tennis motion sequence, and be more consistent with the expert subjective scoring standard.

2.4. Pace adjustment for table tennis players

This subsection first systematically outlines the basic paces in table tennis technology, firstly, image preprocessing of its samples, then quantitatively analyze the characteristics of each pace of table tennis players based on the improved DTW algorithm table tennis player pace feature extraction, and finally, compare the difference between table tennis players' training paces and the standard paces, and point out the deficiencies of table tennis players' paces, so as to achieve the effect of assisting the pace training and rapid improvement of table tennis players' pace level.

2.4.1. Basic pace in table tennis technique

In table tennis, the ball is in constant motion and we need to teach students to change their footwork to adjust their body position. There are several basic steps that are often practiced in lessons and drills, such as the single step, stride, parallel step, hopping step, and crossover step in table tennis.

(1) Single step

This is relatively simple. The specific method of movement is to take one foot as the axis and move the other foot forward, backward, left and right in different directions, with the center of gravity of the body then falling on the moving foot.

(2) Striding

Its moving method is: one foot stirs the ground, the other foot takes a big step in the moving direction, the stirring foot then follows with a half step or a small step, and the center of gravity of the body is moved to the stepping foot.

(3) Parallel stance

Its moving method is: one foot first to the other foot and half a step or a small step, the other foot in the parallel foot landing immediately after the ball to move a step.

(4) Jumping step

The method of movement is: from the ball to the opposite side of the foot stomps the ground, both feet off the ground at the same time to the direction of the incoming ball jumping.

(5) Crossover

This method is more complicated, the specific method is: the foot close to the direction of the incoming ball as the supporting foot, the toe of the foot adjusted to point to the direction of movement, away from the direction of the incoming ball foot in front of the body cross, to the direction of the incoming ball to take a big step, the body then to the direction of the incoming ball to rotate, the supportive foot followed by the incoming direction of the ball and then take a step, which is the front cross step. The back crossover is done behind the body.

2.4.2. Accused pace reduction algorithm

The Controlled Pace Reduction Algorithm is designed to realize the reduction of each pace of a table tennis player during the training process of the actual controlled pace, to quantitatively analyze the running information of each pace of the table tennis player, to compare the difference between the training pace of the table tennis player and the standard pace, and to point out the deficiencies of the table tennis player's pace, so as to achieve the effect of assisting the pace training and improving the pace level of the table tennis player quickly. The results are summarized as follows.

Comprehensive image recognition technology and biomechanical theory to establish x, y, z of the spatial right-angle coordinate system, in which the z-axis is perpendicular to the ground, taking into account the controlled pace is based on the ground of the marching two-coordinate plane of the parameter, so ignoring the table tennis player lifting his foot and landing is the footsteps in the plane of the table tennis training ground across the distance, i.e., ignoring the data of the z-axis of the image processing technology equipment, and directly calculating the x, y-axis based on the ground of the two-dimensional plane of the next parameter information.

The reduction algorithm of the controlled pace is to detect the starting and stopping points of each step of the table tennis player's training, and on the basis of subsection 2.3.2 (feature extraction), to carry out the processing of data fitting, integrating, coordinate calibration, etc., and finally to obtain the size of x, y-axis parameter of each step as well as the moving time of each step.

The detection and segmentation algorithm of running start/stop point adopts the image recognition technology based on image segmentation, i.e., a section of running distance acceleration and angular velocity image data is segmented into a series of different lengths, and the starting moment of each sequence is the lifting time point and the landing time point of one step of the running, respectively. Since table tennis is accompanied by the increase and decrease of acceleration and angular velocity at the starting and stopping moments of running, this project adopts the image segmentation-based approach. Therefore, this topic adopts the controlled pace reduction algorithm based on image segmentation, and the algorithm flow is shown in **Figure 2**. A fixed-width sequence is used as an interval for edge detection, and the starting and landing of a single running pace is determined by detecting the relationship between the magnitude of acceleration (angular velocity) and the threshold value within the interval.

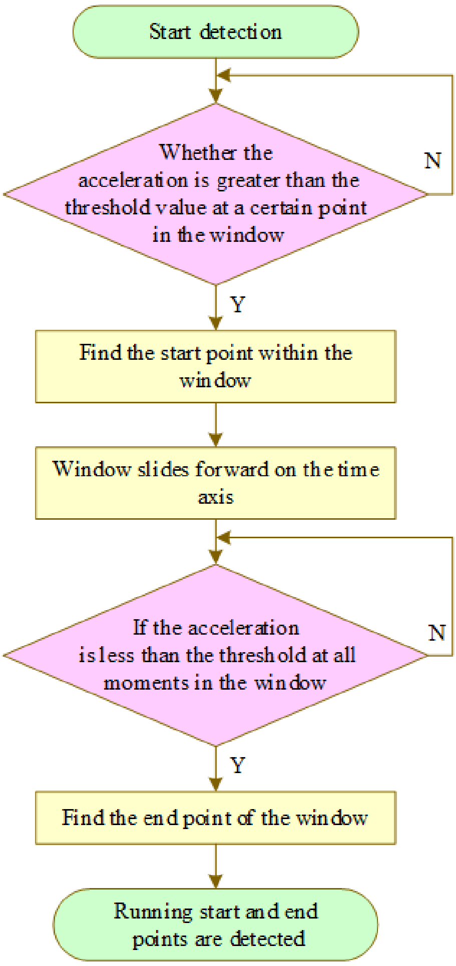


Figure 2. Algorithm flow.

The detection effect of running start and end points is shown in **Figure 3**, where the purple and orange lines indicate the x-axis and y-axis acceleration components, respectively, and the circles indicate the running start and end points detected by the algorithm. It can be seen that the algorithm can accurately detect the starting and stopping points of each running pace, and the x-axis and y-axis acceleration components are distributed in the range of [−0.5, 0.7].

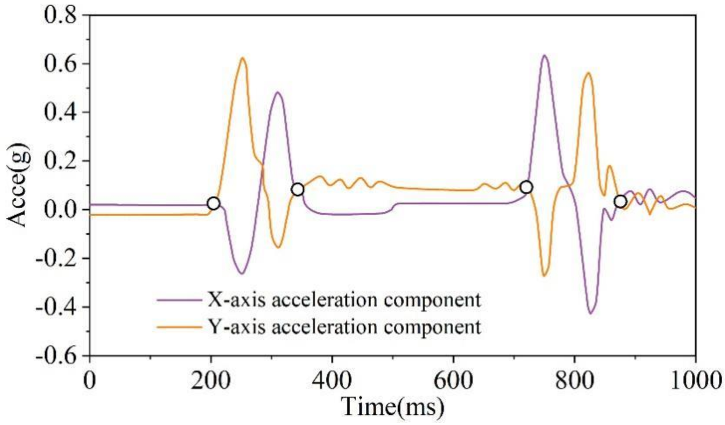


Figure 3. Running start and stop point detection effect.

It should be noted that the coordinate system established in the table tennis venue is constant, while the linear direction of the x, y-axis in the coordinate system of the equipment itself changes dynamically with the pace of movement, because the image recognition technology extracts the relevant motion data relative to the coordinate system of the equipment itself, it is necessary to speak of the angle of deflection and the displacement of the equipment's own coordinate system in each time interval Δt, decomposed into the direction of the x, y-axis in the venue's coordinate system. Therefore, it is necessary to decompose the offset angle and displacement of the coordinate system of the equipment itself into the direction of the 3-axis of the field coordinate system in each time interval 2, obtain the actual coordinate information and deflection angle in the time interval, and set the coordinate information of the x, y-axis of the field coordinate system in each time interval, which is the final pace of movement coordinate information.

The specific formula of the algorithm is as follows:

$$v_{x'}(t) = \int_0^t a_{x'}(t)dt \tag{10}$$

$$S_{x'}(\Delta t_j) = v_{x'}\left(\sum_{j=1}^{i} \Delta t_j\right) \cdot \Delta t_i i = 1,2,\cdots,n \tag{11}$$

$$S_x\left(\Delta t_1\right) = S_{x'}\left(\Delta t_1\right) \tag{12}$$

$$\theta(\Delta t_1) = \omega_x(\Delta t_1) \cdot \Delta t_1 \tag{13}$$

$$\theta(\Delta t_{i+1}) = \theta(\Delta t_i) + \omega_x(\Delta t_{i+1}) \cdot \Delta t_{i+1} i = 1,2,3, \cdots n - 2 \tag{14}$$

$$S_x\left(\Delta t_{j+1}\right) = S_{x'}(\Delta t_{i+1}) \cdot \cos\theta\,(\Delta t_i) + S_{y'}(\Delta t_{i+1}) \cdot \sin\theta\,(\Delta t_i) \tag{15}$$

$$S_y(\Delta t_{i+1}) = S_y(\Delta t_{i+1}) \cdot \cos\theta\,(\Delta t_i) - S_{x'}(\Delta t_{i+1}) \cdot \sin\theta\,(\Delta t_i) \tag{16}$$

$$t_0 = \sum_{i=1}^{n} \Delta t_i \tag{17}$$

$$S_x\left(t_0\right) = \sum_{i=1}^{n} S_x\left(\Delta t_i\right) \tag{18}$$

$$S_y\left(t_0\right) = \sum_{i=1}^{n} S_y\left(\Delta t_i\right) \tag{19}$$

The distance metric function uses the Euclidean distance metric, which is the average of the corresponding Euclidean distances between data points in each frame of the sequence:

$$d = \frac{1}{N} \sum_{n=1}^{N} |J_n - J_n'| \tag{20}$$

In the formula, N is the total number of data points in the sequence, n is the data node, J_n is the data information of the n th data node in the sequence, and J_n' is the data information of the n th data node in another sequence. If the similarity is more than 60%, it is considered to be basically in line with the standard of pace action, and if it is less than 60%, it is considered that there are some problems with the pace action.

3. Research and analysis on pace adjustment of table tennis players

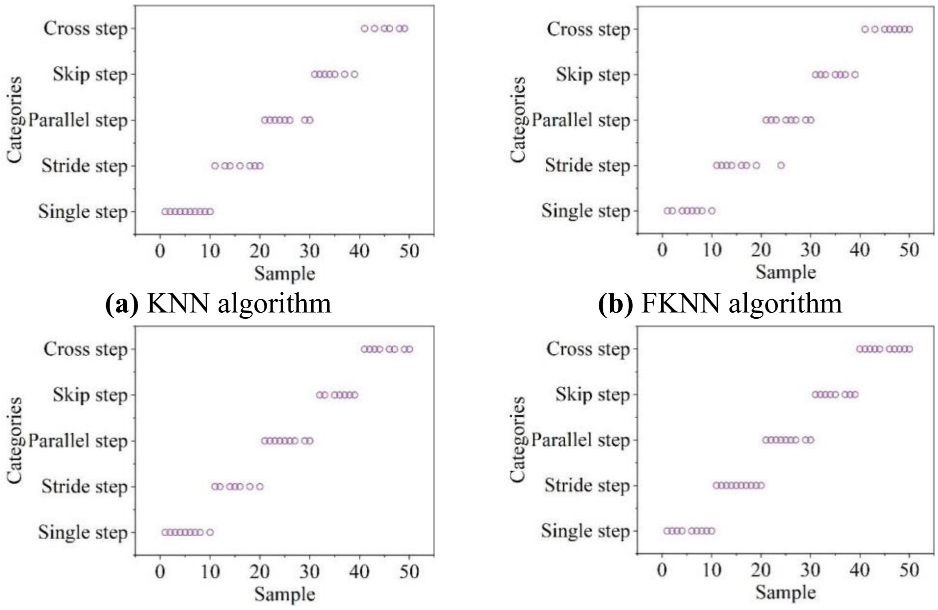
3.1. Feature extraction analysis

3.1.1. Experimental configuration

A Lenovo personal laptop, CPU (Central Processing Unit) model Intel Core i5 2350M, CPU frequency of 2.3 GHZ, memory capacity of 8 GB. Windows 7 operating system, WPF (Windows Preseatation Foundation) user interface framework, which provides a unified programming model, language, and framework, which truly separates the work of the interface designer and developer, and at the same time, it provides a new multimedia interactive user graphical interface.

3.1.2. Analysis of experimental results

Firstly, all the images are prepared for preprocessing and target segmentation, and then 10 images of each table tennis player's pace category (single step, stride, parallel step, hopping step, and crossover step) are selected, and the specific results obtained by using the KNN (K nearest neighbors) algorithm, FKNN algorithm, DTW algorithm, and Improved DTW algorithm (IDTW) respectively for recognizing the above five categories of table tennis player's paces and the recognition accuracy of each method are shown in **Figure 4**. The recognition accuracy of each method, the recognition accuracy results are shown in **Figure 4**, and the recognition rates of different algorithms are shown in **Table 1**, where **Figure 4a–d** represent the KNN algorithm, FKNN algorithm, DTW algorithm, and improved DTW algorithm, respectively. Comprehensive **Figure 4** and **Table 1** show that KNN algorithm has better recognition performance in classification recognition algorithms with more confusion in stride, merge, skip, and crossover steps. The improved DTW-based algorithm proposed in this paper also improves the recognition rate on the original basis, and has better accuracy in the recognition of table tennis player's pace, with an overall recognition accuracy of 92.00%, which provides data support for the biomechanical analysis of table tennis player's pace in the following.



(a) KNN algorithm **(b)** FKNN algorithm

(c) DTW algorithm **(d)** IDTW algorithm

Figure 4. Recognition accuracy result.

Table 1. Different algorithm recognition rate.

Name	KNN	FKNN	DTW	IDTW
Single step	10/10 = 100.00%	8/10 = 80.00%	9/10 = 90.00%	9/10 = 90.00%
Stride step	7/10 = 70.00%	7/10 = 70.00%	7/10 = 70.00%	10/10 = 100.00%
Parallel step	8/10 = 80.00%	9/10 = 90.00%	9/10 = 90.00%	9/10 = 90.00%
Skip step	7/10 = 70.00%	7/10 = 70.00%	7/10 = 70.00%	9/10 = 90.00%
Cross step	6/10 = 60.00%	8/10 = 80.00%	8/10 = 80.00%	9/10 = 90.00%
Total	38/50 = 76.00%	39/50 = 78.00%	40/50 = 80.00%	46/50 = 92.00%

3.2. Biomechanical analysis

In this study, the above extracted pace characteristics of table tennis players (parameters acceleration and angular velocity) were time-normalized to obtain the mean-time curve of the angles of all subjects, so as to gain a deeper understanding of the biomechanical laws of the pace of table tennis players by analyzing the changes of acceleration and angular velocity of each motion link of the foot and ankle during the whole process of the foot force. Due to the limited space, the biomechanical analysis of table tennis players' stride step is analyzed as follows from the five table tennis players' stride characteristics of forehand stride step as an example:

3.2.1. Acceleration

Combined with the biomechanical theory, the acceleration change rule of forehand stride action is explored, and the acceleration time curve is shown in **Figure 5**. It can be clearly seen that in the first force stage, the acceleration of the vertical reaction force of the ground reaches the first peak value (0.387 m/s^2) when the table tennis player lands on the ground after the striking foot and actively adjusts the center of gravity of the body according to the incoming ball. In the second stage of force application, the force of vertical reaction force on the ground reached the first peak (0.387 m/s^2) when the power foot was actively stomped and extended to complete the striking action and then stomped off the ground to return to the initial position. The second peak acceleration (0.293 m/s^2) occurs during this process. It shows that when a table tennis player performs a stride step, the striking force-generating foot first takes a big step according to the direction of the incoming ball, and then the center of gravity of the body is shifted to the striking force-generating foot after the landing.

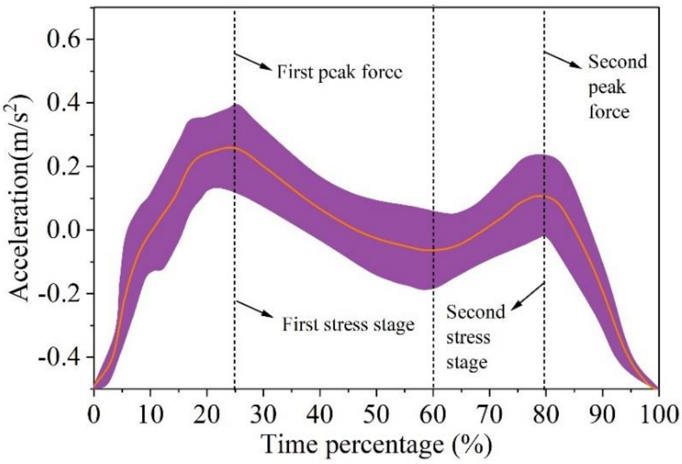


Figure 5. Acceleration time curve.

3.2.2. Angular velocity

Based on the improved DTW algorithm of table tennis player's pace feature extraction, the angular velocity of forehand stride action is obtained, and the angular velocity of forehand stride action is investigated with the help of biomechanical theory, and the angular velocity time curve is shown in **Figure 6**. As can be seen in **Figure 6**, when the table tennis player performs the forehand stride, the foot basically does not turn over when the striking foot hits the ground. However, after landing, the center of gravity of the body is transferred to the striking foot, the force on the foot increases and changes to the valgus state, and the Achilles tendon angular velocity decreases to reach the minimum value, while the ankle dorsiflexion and extension angular velocity increases, and the ankle joint does plantarflexion movement. After the Achilles tendon angular velocity reaches the maximum external rotation angular velocity, it starts to increase, when the first peak force appears, the foot is doing internal rotation, the ankle joint is in dorsiflexion, the toe extension angular velocity decreases rapidly, and the striking force-generating foot enters into the stage of center of gravity adjustment of the full-foot support. At the end of the first stress stage, the striking foot enters the second stress stage. With the active extension of the striking foot, the force on the foot increases, the Achilles tendon angular velocity starts to decrease, the foot does valgus movement, and the ankle joint continues to do dorsiflexion movement, when the foot reaches the maximum valgus of the second force stage and the ankle joint reaches the maximum angular velocity of dorsiflexion, the second peak force appears, and then the striking foot starts to extend away from the ground, and the ankle flexion angular velocity increases, and the ankle joint does active plantarflexion, and the maximum ankle dorsiflexion angular velocity is reached in the moment of leaving the ground. At the moment of ground release, the maximum angular velocity of ankle flexion is reached. In the stomping off the ground stage when the toe and metatarsophalangeal joints are on the ground and the heel is raised, the toes start to make maximum toe extension around the metatarsophalangeal joints, and along with the increase of the toe extension angular velocity is the increase of the Achilles tendon angular velocity, and the foot does inward turning movement, and the foot is transformed from an outward turning state to the initial state at the moment of landing.

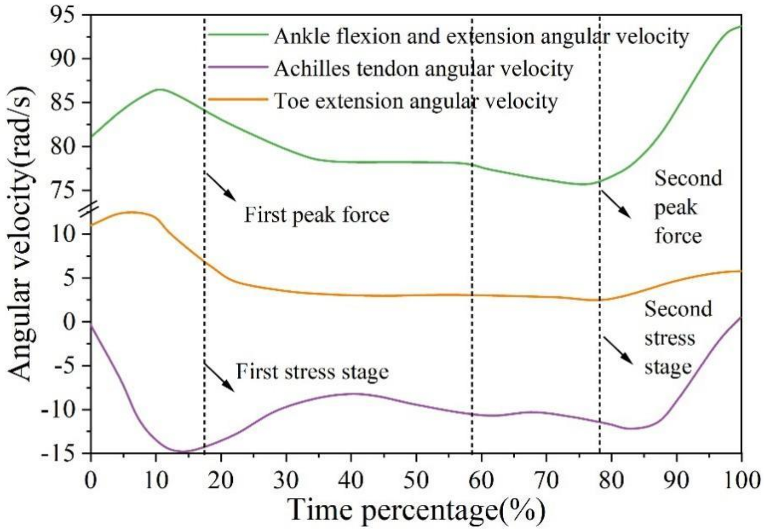


Figure 6. Angular velocity time curve.

3.3. Analysis of the application of the controlled pace reduction algorithm

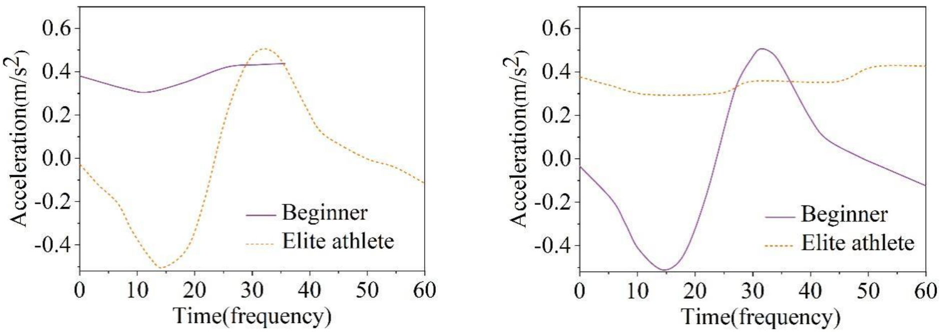
Using the controlled pace reduction algorithm to calculate the similarity of the acceleration and angular velocity of the right hip joint in the three directions of *X*, *Y*, and *Z* axes during the pace action of the straight racket cross-court shot pulling downspin arc circle ball technique of the beginners and the pace action of the excellent athletes, the similarity of the kinematic parameters of the right hip joint point for diagnosis of the pace action is tested as shown in **Table 2**. It can be seen that in the similarity calculation between the pace action of table tennis beginners' straight paddle cross-hitting and pulling downspin arc ball technique and the standard pace action of excellent athletes, the similarity of acceleration of the right hip joint point in the *X*-axis direction is 0.729, and the similarity of acceleration in the *Z*-axis direction is

0.618, which is greater than 0.6, indicating that in the *X*-axis and *Z*-axis directions, the trajectory of the right hip joint of the beginners' right hip is more similar to that of the standard action model of the excellent athletes. The similarity of the angular velocity of the right hip joint point in the *X*-axis direction is 0.677, and the similarity of the angular velocity of the right hip joint point in the *Z*-axis direction is 0.609, which are both greater than 60%, indicating that the trajectory of the right hip joint of beginners in the *X*-axis and *Z*-axis directions is more similar to the standard movement model of excellent athletes. On the other hand, the similarity of acceleration in the *Y*-axis direction of the right hip joint point is 0.524, and the similarity of angular velocity in the *Y*-axis direction of the right hip joint point is 0.511, which are both smaller than 0.6, indicating that there are certain problems in the acceleration in the *Y*-axis direction and angular velocity in the *Y*-axis direction of the right hip joint point during the pace action, therefore, the acceleration in the *Y*-axis direction and the angular velocity in the *Y*-axis direction of the right hip joint point in the pace action of the beginner's straight racket horizontal hitting and pulling downward-spinning curved loop technique are not suitable for beginners. Acceleration and angular velocity in the *Y*-axis direction are analyzed in detail.

Table 2. Kinematic parameter similarity test.

Kinematic parameter	*X*-axis direction similarity	*Y*-axis direction similarity	*Z*-axis direction similarity
Acceleration	0.729	0.524	0.618
Angular velocity	0.677	0.511	0.609

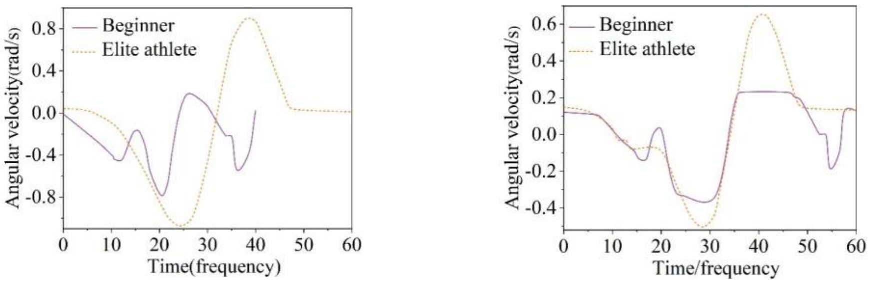
The comparative analysis of *Y*-axis acceleration at the right hip joint point is shown in **Figure 7**, **Figure 7a,b** are the original curves, and the adjusted curves, respectively. The pace movements of the right hip joint *Y*-axis acceleration of the excellent athletes totaled 60 frames, while the pace movements of the beginners totaled 37 frames, and the length of the movements was shorter relative to the excellent athletes. In the lead-in phase, the time of the excellent athlete is 0–13 frames, while the length of the action sequence of the lead-in phase of the beginner is 0–9 frames. The acceleration of the right hip joint point of the beginner in the *Y*-axis direction of movement in the lead-in phase has a big difference with the pace of the excellent athlete, and the acceleration of the right hip joint of the beginner is smaller, which indicates that the pace action of the beginner table tennis player turning to the left is not obvious in the lead-in phase. In the swing and follow-through phases, the time phase of the excellent athletes' pace movements was 13–34 frames, while the beginners' swing and follow-through phases were 9–29 frames. However, the value of the acceleration change of the excellent athletes in the swing and follow-through phases was 1.1 m/s^2, while the value of the acceleration change of the beginner table tennis players in this phase was only 0.069 m/s^2, which is comparable to the standard pace movements of the excellent athletes. The change of acceleration ratio in the *Y*-axis direction during the swing and follow-through phases of the table tennis beginner's right hip joint is very small. During the pacing action of the table tennis beginner in the straight horizontal stroke pulling downspin arc ball technique, the center of gravity of the swinging action is not obvious in the swinging action phase, and the swinging action mainly relies on the arm of the racket holder to swing the racket to hit the ball, which affects the quality of the beginner's batting to a large extent. In the reduction stage, because the beginner in the pace action process of the right hip joint point in the direction of the *Y*-axis of the lead phase and swing bat, with the swing phase acceleration change amplitude is too small, so the beginner's right hip joint can not reflect the reduction stage.



(a) Original curve **(b)** Adjusted curve

Figure 7. Comparative analysis of *Y*-axis acceleration at right hip joint.

The comparative analysis of the *Y*-axis angular velocity of the right hip joint point is shown in **Figure 8**, **Figure 8a,b** are the original curve, and the adjusted curve, respectively. In the lead-in phase, there are fluctuations in the change of the angular velocity of the right hip joint point for beginners, and in the *Y*-axis direction, the change of the angular velocity of the right hip joint point is relatively small and short. In the stage of swinging to hit the ball and the stage of following the swing, the speed change was smaller, and the right hip joint speed was slower in the hitting section, which indicated that the beginners had poorer effect of turning the waist and generating the power angle when swinging to hit the ball. In the restoration stage, the right hip joint has a slight wobble. The slower angular velocity of the right hip joint of the beginner table tennis players in the technical action process, combined with the above analysis of the *Y*-axis angular velocity of the hip joint, can indicate that the center of gravity conversion is not obvious in the structure of the beginner's action, which affects the process of the action of force generation, and thus affects the quality of the stroke. The controlled pace reduction algorithm is able to analyze and diagnose the pace action of the table tennis beginner's horizontal pulling downspin arc ball technique, and provides certain ideas and reference basis for the intelligent development of the table tennis pace action adjustment.



(a) Original curve **(b)** Adjusted curve

Figure 8. Comparative analysis of *Y* axis angular velocity of right hip joint.

From the difference between the acceleration and the angular velocity of the ball of the beginner and the professional athlete, the professional table tennis players are more skilled in the swing and pace. The results show the great advantages of biomechanical analysis on the pace of table tennis players.

4. Conclusion

This paper utilizes the theory of sports biomechanics and image recognition technology to investigate the pace adjustment of table tennis players. It provides a new analysis method for the diagnosis of table tennis players' pace movements, which is innovative in this field.

Firstly, in the process of feature extraction and analysis, the improved DTW algorithm proposed in this paper has excellent performance in table tennis players' pace features, and its overall recognition accuracy is 92.00%, which is much better than the other three algorithms (KNN algorithm, FKNN algorithm, DTW algorithm).

Secondly, through the biomechanical analysis of table tennis player's pace, it can be seen that the acceleration of the vertical reaction force of the ground reaches the first peak value (0.387 m/s^2) when the table tennis player's striking power foot lands on the ground and adjusts the center of gravity of the body according to the incoming ball situation, and the second peak acceleration value (0.287 m/s^2) occurs when the striking power foot actively stomps and extends to participate in completing the striking action and then stomps away from the ground to return to the initial position. At this time, the second peak acceleration (0.293 m/s^2) occurs, which perfectly reproduces the acceleration rule of forehand stride. At the same time, the angular velocity of Achilles tendon decreases and reaches the minimum value, while the angular velocity of ankle flexion and extension increases, and the ankle joint does plantarflexion movement. In summary, it can be seen that the need to constantly strengthen the flexibility and suppleness of the athlete's stride is an important condition to improve the table tennis player's skills.

Finally, the similarity of acceleration in the *X*-axis direction of the right hip joint point is 0.729, and the similarity of acceleration in the *Z*-axis direction is 0.618, which are both greater than 0.6, and the corresponding angular velocities are 0.729 and 0.609, respectively, and only the acceleration and angular velocity in the *Y*-axis direction are less than 0.6, which indicates that there are certain problems with acceleration in the *Y*-axis direction of the right hip point and the angular velocity in the *Y*-axis direction in the course of the stride movements.

Ethical approval: Not applicable.

Conflict of interest: The author declares no conflict of interest.

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