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RESEARCH ARTICLE

Tactical Analysis of Table Tennis Video Skills Based on Image Fuzzy Edge Recognition Algorithm

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ABSTRACT To improve the effect of table tennis tactical analysis, this study proposed a table tennis video tactical analysis method based on image fuzzy edge recognition algorithm. This algorithm can effectively recognize edges in images to improve recognition accuracy and reduce errors and rejection rates. In addition, this research combines the methods of target tracking and trajectory estimation to build a table tennis video game tactical analysis platform. The experimental data show that the recognition accuracy of the proposed fuzzy edge recognition algorithm is 98.1%, and the error and rejection rates are less than 1.6%. Compared with the image edge detection algorithm based on interval value fuzzy, the proposed algorithm has better performance. When the positioning error is 10%, the precision of the table tennis target tracking algorithm can reach 94.3%, which is 9.3% higher than that of the direct linear transform algorithm. The table tennis video game tactical analysis platform can analyze the velocity of ping-pong ball according to the video, and records the droppoint of ping-pong ball, which helps the players to develop more effective tactics and strategies to improve their competitive level and achievements.

INDEX TERMS Image processing, fuzzy edge recognition, target tracking, trajectory estimation, ping-pong ball tactics.

I. INTRODUCTION

Ping-pong ball, as a worldwide popular sport, has the characteristics of fast, flexible and technical. Therefore, it has important research value in the analysis of football skills and tactics [1]. In ping-pong ball match, the players' technical level and tactical choice directly affect the result of the match. Therefore, the analysis and research of skills and tactics in ping-pong ball matches are of great significance for improving players' competitive level and defeating opponents [2]. However, in the existing analysis of table tennis matches, there is still a lack of in-depth research on the impact of athletes' technical level and tactical choices on match results. Recently, image analysis has been widely used in the field of sports [3]. Image analysis technology can track and analyze the movements of players and the trajectory of the ball to provide detailed information about the player's technical level and tactical choices [4]. However, the current technical and tactical analysis methods of ping-pong ball are mainly using the player's movement trajectory and the ball's movement trajectory, ignoring the influence of the ball's edge information on the ball's skills and tactics [5]. Traditional methods for analyzing the trajectory of athletes and balls cannot fully reveal the impact of ball edge information on technical strategies. In ping-pong ball, the edge information of the ball is crucial for athletes to judge and respond to opponent tactics. Traditional methods have low efficiency in processing and analyzing large amounts of image data, which are easily affected by external factors. The traditional analysis methods of table tennis techniques and tactics are usually conducted after the game, which cannot provide real-time and effective tactical guidance for athletes during the game. In addition, traditional methods rarely consider individual differences, making it difficult to provide

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personalized recommendations based on the characteristics and needs of athletes. Therefore, based on the image fuzzy edge recognition algorithm, combined with relevant tracking and measurement methods, this study builds a ping-pong ball skills and tactics analysis platform, aiming to provide more accurate technical guidance and tactical suggestions for ping-pong ball players. The contribution of this study is that, by extracting and analyzing the edge information of the ball in the video of ping-pong ball match, the trajectory of the ball and the skill level of the player can be judged more accurately. Meanwhile, by tracking and analyzing the edge information of the ball, more information about the players' tactical choices can be provided to help the players make more effective tactical strategies. The research consists of four parts, the first part is related research, the second part is the method of ping-pong ball video game tactical analysis method, the third part is the experimental analysis of ping-pong ball video game tactical analysis method, and the fourth part is the conclusion of the whole study.

II. RELATED WORKS

Image processing refers to the process of digital processing and analysis of images. By using computer algorithm and technology, the image can be enhanced, restored, segmented, feature extraction and other operations to obtain clearer and more useful image information. For green tea image recognition, Chen's research team used multi-layer perceptual neural networks, support vector machine regression algorithm and genetic algorithm to predict the chemical composition. The search performance of the regression vector machine model based on genetic algorithm was better [6]. Schmidt research team proposed a background oriented Schlieren image processing method based on wavelet optical flow analysis. In this method, wavelet optical flow analysis was used to improve the spatial resolution, so as to play the advantages of optical flow processing. Experimental results showed that this method could improve the sensitivity of background oriented schlieren image processing by 15% [7]. B. E. Schmidt and M. R. Woike used image processing technology to analyze the color of aquaculture water, and combined machine learning, fusion random vector function chain network and data processing grouping method to propose an intelligent water quality monitoring method. Characteristic data set experiments showed that the average prediction accuracy of this method could reach 96% [8]. Zhou et al. proposed a color-preserving method. This method stretched the pixel value of the input image to the edge of the RGB color space. The results showed that the algorithm could recover the color of the image well and obtain higher saturation [9]. Aiming at image processing of defocusing fuzzy droplets, Wang's research team combined deep learning algorithms to restore clear images and infer depth information, and simulated defocusing images of droplets using synthetic fuzzy data generated by Gaussian kernel method. The diameter relative error of this model was less than 5%, and the position error was less than 1mm [10].

Ping-pong ball video game tactical analysis is based on the observation and analysis of ping-pong ball game video, to understand the players' skill level and tactics. Qiao proposed along short-term memory (LSTM) model for real-time trajectory recognition and tracking of ping-pong ball in different environments. The model used deep reinforcement network to extract real-time motion characteristics and combined LSTM to predict the trajectory of the ball. The results showed that, the performance of convolutional neural network LSTM model based on deep learning was enhanced by 23.17% [11]. Zhao research group proposed a trajectory tracking algorithm for ping-pong ball targets based on machine vision and proportional conjugate gradient. In this method, a deep neural network algorithm model was created by extracting 10 frames of position and speed information for feature selection. The real man-machine game data was obtained by using 20 frames of continuous position information for training. The results showed that this algorithm was more suitable for ping-pong ball robot system [12]. Yang's team proposed a hit analysis method based on deep reinforcement learning for ping-pong ball tactical analysis, and developed a virtual ping-pong ball match environment to collect various simulation data. The accuracy of this model could reach 70% [13]. Li et al. used deep learning method to analyze the rotating trajectory of ping-pong ball balls, combined with spatial sampling and reconstruction encoders and LSTM to analyze the trajectory of ping-pong ball balls. Experiments showed that this method could predict the rotation trajectory of ping-pong ball with an precision of 96.5% and a velocity of 15s [14].

To sum up, many researchers have put forward a lot of research and design for image processing and tactical analysis of ping-pong ball video skills, but the scope of application of these algorithms and systems still needs to be improved. The common issues in the above studies mainly lie in the accuracy and stability of the model. Due to the complexity and uncertainty of video data in table tennis matches, these models still have certain errors and uncertainties when processing table tennis match video data. In addition, these studies also have certain limitations, such as a lack of real-world scenarios and datasets for competitions, as well as a lack of consideration for the impact of other factors such as athlete status and competition environment. Therefore, this study proposes a ping-pong ball video game tactical analysis based on image fuzzy edge recognition algorithm, aiming to enhance the effect of image recognition model and the effect of ping-pong ball video game tactical analysis.

III. DESIGN OF PING-PONG BALL VIDEO GAME TACTICS ANALYSIS METHOD

This section designs the tactical analysis methods of ping-pong ball video skills, including ping-pong ball image fuzzy edge recognition algorithm, ping-pong ball target tracking method, ping-pong ball spatial information estimation and trajectory prediction method and ping-pong ball rotation measurement method, and designs the tactical analysis platform of ping-pong ball video skills.

A. DESIGN OF FUZZY EDGE RECOGNITION ALGORITHM FOR PING-PONG IMAGES

In ping-pong video image processing, it is required to enhance the image to ensure the quality of the image and the accuracy of edge feature extraction [15]. In this study, the continuous wavelet transform is obtained by translating and scaling the basic wavelet with wavelet transform to enhance the image. The basis of wavelet transformation of ping-pong images is shown in Equation (1).

$$We(a,b) = < e, \varphi_{a,b} > = \int_{-\infty}^{+\infty} e(t)\frac{1}{\sqrt{b}}\varphi\left(\frac{t-a}{b}\right)dt \quad (1)$$

In Equation (1), the wavelet transform equation of the ping pong image is We; Ping-pong ball image coordinates are (a, b); The basic wavelet transform is $e(t)$; The Fourier transform is $\varphi(\omega)$. The basic wavelet higher-order calculation of function values and mean values that are not in the domain is shown in Equation (2).

$$\begin{cases} H = \int_{-\infty}^{+\infty} \varphi(t)dt = 0 \\ M = \int_{-\infty}^{+\infty} t^u \varphi(t)dt = 0, u = 0, 1, \ldots, N-1 \end{cases} \quad (2)$$

In Equation (2), the function values and average values that are not in the domain of definition are H and M respectively. The basic wavelet after translation and contraction processing is shown in Equation (3).

$$\varphi_{s,u}(t) = 2^{-s/2}\varphi(2^{-s}t - u), \quad s, u \in Z \quad (3)$$

In Equation (3), the wavelet function set contraction function and translation function are s and u respectively. The image decomposition equation completed in the wavelet domain function is shown in Equation (4).

$$E_{hp}(a,b) = E(a,b) - E_{\eta p}(a,b) \quad (4)$$

In Equation (4), the high-frequency component is $E_{hp}(a, b)$; The low frequency component is $E_{\eta p}(a, b)$. The transmission equation of the low-frequency component is shown in Equation (5).

$$E_{\eta p}(a,b) = H_{\eta p}(a,b)E(a,b) \quad (5)$$

In Equation (5), the transmission function of the low-frequency component is $H_{\eta p}(a, b)$, and the image enhancement of the wavelet transform is shown in Equation (6).

$$H_{hp}(a,b) = 1 - H_{\eta p}(a,b) \quad (6)$$

In Equation (6), the transmission function of the high-frequency component is $H_{hp}(a, b)$, and the transmission equation for adding the processed high-frequency component to the original figure is shown in Equation (7).

$$H_{hpo}(a,b) = a + bH_{hp}(a,b) \quad (7)$$

In Equation (7), the high-frequency component of the original image after processing is $H_{hpo}(a, b)$, so as to complete the ping-pong image enhancement, and then it will be used for edge feature extraction. Before extracting edge features of ping-pong machine image, it is necessary to determine the center point of image and regard it as the effective region for extracting edge features. The central point position is calculated as shown in Equation (8).

$$\upsilon_k = \tan^{-1}\frac{\sum_{i=1}^{8}\sum_{i=1}^{8} 2G_x(i,j)G_y(i,j)}{\sum_{i=1}^{8}\sum_{j=1}^{8}(G_x^2(i,j) - G_y^2(i,j))} + \frac{\pi}{2} \quad (8)$$

In Equation (8), the position of center point of ping-pong image is υ_k; Ping-pong ball image matrix is $A(i, j)$; The fingerprint image after Gauss low-pass filtering is $A'(i, j)$; The direction field matrix is $G(i, j)$; The number of non-overlapping area blocks divided according to 8×8 size is k. In this study, 3-order Haar wavelet decomposition was used to process the effective region to extract the edge features of ping-pong ball images and save them for fuzzy edge recognition of ping-pong ball images [16]. Probabilistic neural network (PNN) is used to identify the fuzzy edges of ping-pong images, and the recognition results are shown in Equation (9).

$$\begin{cases} D_i(y) = \frac{p(i)}{M_i}\sum_{j=1}^{M_i}\exp(-\frac{1}{\gamma^2})l^2(x_j^{(i)}, y)) \\ l^2(x_j^{(i)}, y) = \sum_{k=1}^{n}(y(k) - x(k)_j^{(i)})^2 = \sum_{k=1}^{n} l(k)^2 \end{cases} \quad (9)$$

In Equation (9), the number of output edge feature vectors is M_i; The prior probability is $p(i)$; The distance between the k-th pair of edge feature samples is $l(k)$; The smoothing parameter is γ; The identification result is $D_i(y)$.

B. DESIGN OF PING-PONG BALL TARGET TRACKING METHOD

After the detection and recognition of ping-pong balls, the ping-pong balls in the video need to be tracked to facilitate subsequent spatial information estimation and trajectory prediction [17]. This study applies a tracking framework that scales the input image to a size of 100×100, and finally outputs a 50×50 matrix. The overall network structure of the tracking model is shown in Figure 1.

Tracking targets can determine whether the pixels in the corresponding area of the grid belong to the different values in the matrix [18]. To more accurately represent the target object in the original input, thresholds are set to generate a probability plot of the connected region. In this connected region, the probability value of pixels is significantly higher than the connection parts outside the area [19]. To extract more position information, the input image is processed by a convolution layer and a spatial pyramid pool layer, and the receptive field of each pixel in the output layer is larger.

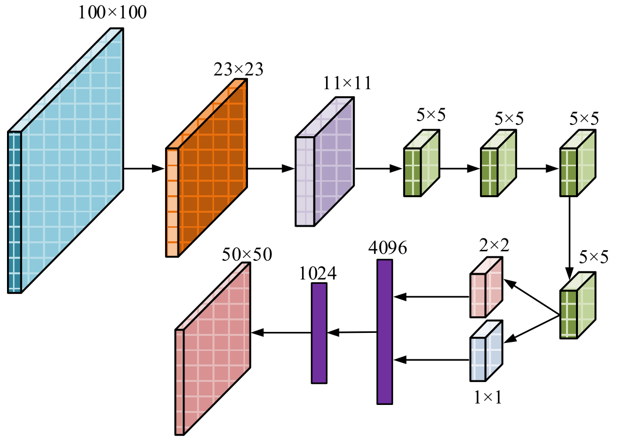


FIGURE 1. The overall network structure of the tracking model.

In addition to output the target position, it is required to perform a binary classification to further distinguishing target objects. In this way, the target can be located more accurately and the target can be tracked effectively. The definition of the loss function is shown in Equation (10).

$$L(p_g, n_l) = L_{cls}(n_l, n_l^*) + \lambda \sum_{i=1}^{50} \sum_{i=1}^{50} \sum_{j=1}^{50} -(1 - t_{i,j}) \log(1 - p_{g_{i,j}}) - t_{i,j} \log(p_{g_{i,j}}) \quad (10)$$

In Equation (10), the output probability value and category score are p_g and n_l respectively; The output category is n_l^*; $t_{i,j}$ indicates whether the actual target probability graph is a target pixel; The regularization term is scaled to λ. For parts of the probability graph output involving the target object, if the probability is much higher than other unconnected regions, these parts will appear as white connected regions. Direct processing of the probability graph can improve the speed, but the precision of the bounding box is not high, there are two reasons: Firstly, the matrix size of each pixel is 2×2. And the object boundary is rough; Secondly, a simple threshold can be used to determine the target pixel [20]. Inaccurate bounding boxes accumulate errors during tracking. Background pixels occupy more, resulting in tracking failure or loss of target [21], [22]. Therefore, this study uses a method combining coarse-grained features and fine-grained features, and corrects the differences. The interest region pooling layer is introduced, and the low-level feature map is used as one of the inputs to obtain more detailed features as coarse-grained feature inputs. In addition, a new 7×7 characteristic map is obtained by clipping and scaling the probability graph of the high-level feature extraction according to the position of the bounding box. The coordinates of the bounding box are returned and the 4-dimensional vector is output. The first two dimensions denote the x and y direction offset, while the rest denote the scaling ratio of w and h, with the value range between [0, 1]. To get the frame coordinate regression closer to the real position, the pooling layer of the region of interest is introduced, otherwise the training process will be unstable and cannot converge. Finally, the research takes SmoothL1 function as a loss function, and its definition is shown in Equation (11).

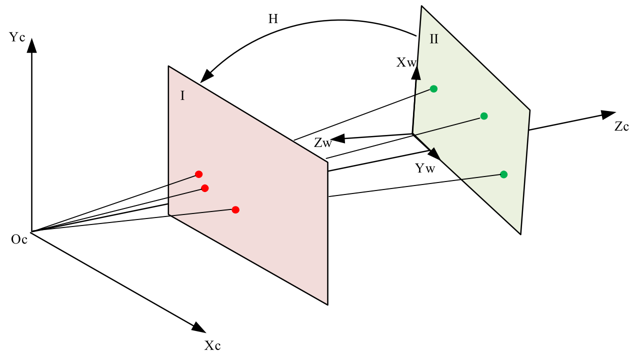


FIGURE 2. The description of spatial point relationships through homography transformation.

$$Smooth_{L1}(x) = \begin{cases} 0.5x, & if\ |x| < 1 \\ |x| - 0.5, & otherwise \end{cases} \quad (11)$$

In Equation (11), SmoothL1 function is $Smooth_{L1}(x)$. The study adopted a strategy of using L2 losses near the origin and L1 losses in other regions to avoid the problem of gradient explosion. By fine-tuning the coordinates of the bounding box after regression, we can obtain more accurate probability graph results.

C. RESEARCH ON SPATIAL INFORMATION ESTIMATION AND TRAJECTORY PREDICTION OF PING-PONG BALL

In this study, the external parameter matrix of the camera is calculated through the single strain exchange. Homologous transformation describes the one-to-one correspondence between a plane in space and a point on the imaging plane. Through homologous matrix, the external parameter matrix of the camera can be calculated. The position of the camera can be estimated using the homography matrix. The description of the relationship between space points by homography transformation is shown in Figure 2.

Toevaluate the internal and External Parameter Matrix(EPM), in addition to the homography matrix of a frame image, the Internal parameter matrix(IPM) is also needed. In this study, the IPM of the camera is pre-calibrated by the standard checkerboard, and the EPM of the camera is estimated by combining the homography matrix and the ball table. By calculating the projection matrix and the box coordinates of the ping-pong ball, the ping-pong ball's spatial positioncan be calculated. However, lens distortion in the actual shot image will lead to errors, so distortion correction is required [23], [24]. Lens distortion is divided into radial distortion and tangential distortion, which can be described by distortion coefficient. Finally, the spatial coordinates of the ping-pong ball can be calculated by the pixel coordinates and depth information after the distortion is removed.

After obtaining the space coordinates of ping-pong ball, it is necessary to predict the motion trajectory. This paper combines recurrent neural networks (RNN) and LSTM networks to construct a prediction model of ping-pong ball trajectory. RNN maintains a state vector internally and processes sequence inputs by constantly updating the state vector [25]. Meanwhile, it outputs a vector based on the current input and current state. Through several recursive operations, the neural network can output a corresponding output sequence. In trajectory prediction, this output sequence is the predicted position of the next frame. Another way to work is to connect the output vector directly to the next input, enabling automatic generation of sequences of arbitrary length. In the model of ping-pong ball robot system, to solve the problem of tracking motion model and trajectory prediction, a new RNN model is needed. For a motion model, a known sequence of ping pong coordinates can be entered into the network to form a prediction of the coordinates for the next frame. For trajectory prediction, the known coordinate sequence needs to be fed into the neural network to update the internal state vector to generate new coordinates. Through this sequence, the landing information and some attributes of the ping pong ball during flightcan be calculated. The status update of RNN is shown in Equation (12).

$$h_t = \tanh(W_{hh}h_{t-1} - W_{xh}x_t) \tag{12}$$

In Equation (12), the updated status is h_t; The state transformation matrix is $W_{hh}h$; The input transformation matrix is W_xh; The output transformation matrix is W_hy. The RNN output is shown in Equation (13).

$$y_t = W_{hy}h_t \tag{13}$$

In Equation (13), the output of RNN is y_t. The formula for updating the RNN weight matrix is shown in Equation (14).

$$\begin{cases} \Delta w_{ih} = \eta\partial L/\partial y \times h \\ \Delta w_{oj} = \partial L/\partial z \times z \\ \Delta w_{ii} = \eta\partial L/\partial u \times u \end{cases} \tag{14}$$

In Equation(14), the connection weight between the input layer and the hidden layer is Δw_{ih}, the learning rate is η, the loss function is L, and the output of the hidden layer is h. The connection weight between the hidden layer and the output layer is Δw_{oj}; the output layer is z. The connection weight between neurons is Δw_{ii}; the output of neurons is u. However, RNNS do not perform well on some sequence problems because their state gradually weakens over the course of recursion. To solve this problem, LSTM introduces new internal state vectors and paths that connect the preceding and following state. Meanwhile, LSTM's activation function enables network learning to retain information about previous states. The LSTM model structure is shown in Figure 3.

The model takes the coordinates of ping-pong balls at time t as input values and outputs multiple multi-dimensional Gaussian distribution parameters. Mixed density networks (MDN) accept the intermediate state of the LSTM as input and output parameters of multiple multidimensional Gaussian distributions. Each Gaussian distribution is represented by seven

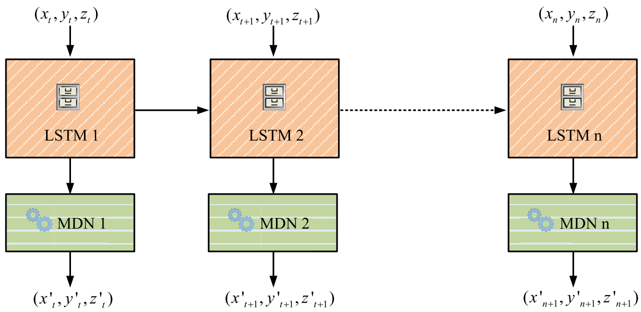


FIGURE 3. Long short-term memory model structure.

parameters. For an MDN with K Gaussian distributions, the probabilities of input state and output speed are shown in Equation (15).

$$\begin{cases} p(v\,|c) = \sum_{k=1}^{K} \theta_k(c) p_k(v\,|c) \\ s.t. \sum_{k=1}^{K} \theta_k(c) = 1 \end{cases} \tag{15}$$

In Equation (15), the probability of input state and output speed is $p(v\,|c)$; $\theta_k(c)$ represents the Gaussian distribution's weight; The corresponding probability distribution function is p_k. The loss function of MDN training is shown in Equation (16).

$$L(v^*, x) = -\log(\sum_{k=1}^{K} \theta_k(c(x)) p_k(v^*\,|c\,(x))) \tag{16}$$

In Equation (16), v^* denotes the target output; x denotes the input 3D coordinates are; The intermediate state after acceptance by the LSTM is $c(x)$. When making trajectory predictions, the model randomly selects a sample and inputs it into the network as a new coordinate. Through many cycles, a predicted trajectory is finally gotten. When the LSTM is applied as a motion model for tracking the frame, different candidate regions are extracted from a mixed Gaussian distribution.

D. RESEARCH ON PING-PONG BALL ROTATION MEASUREMENT METHOD

The judgment of the rotating direction of ping-pong ballis essential in the return of players in the game. Ping-pong ball rotation measurement scene diagram is shown in Figure 4.

To measure the rotation of ping-pong ball, a rotational speed estimation method based on Fourier transform is proposed. The rotation speed is solved by analyzing the periodic change of the pattern on the ball in the video of ping-pong ball rotation. First, the video is pre-processed, and then the Hough circle detection algorithm is used to obtain the spherical coordinates and radii. Then select the color of the pattern on the ball as the statistical target, and calculate the proportion of the color pixels in each frame to the total number of pixels in the ping pong ball. By obtaining enough curves of the proportion of pixels changing with time, the period of the calculated curve is the rotation period of the ping pong ball. This method avoids the difficulty of feature point tracking and

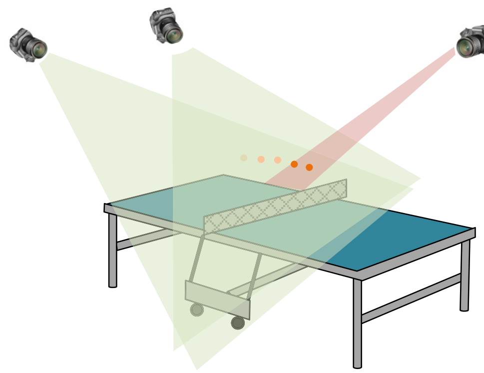


FIGURE 4. Schematic diagram of ping-pong ball rotation measurement scene.

improves the accuracy by using the information of successive multi-frame images.

The method to predict the rotation direction with CNN model is studied. To process the form of the input data, the data needs to be pre-processed to contain sufficient information. For the output, you can choose either the regression problem, which predicts the specific direction of rotation, or the classification problem, which divides the rotation axis into N classes by Angle. In addition, assuming that the axis direction does not change in a short period of time, the problem can be simplified to analyze several consecutive frames of images. Therefore, the problem is transformed into a picture classification problem and solved using the CNN model. First, the input data is processed, the continuous K-frame image is adjusted to the center of the sphere, and these frames are superimposed. These superimposed images are then used as input data. Different axis classifications correspond to different logo shapes, and logos in the same axis classification have similar features. Ping-pong ball images without background noise were extracted, and their rotation axis classification was marked. The CNN model was used for training and prediction. The input of the model is a single image obtained by superimposing multiple consecutive frames of images, and the output is numbered according to the defined category, which is used to predict the rotating axis position of the ping-pong ball.

E. DESIGN OF PING-PONG BALL VIDEO GAME TACTICAL ANALYSIS PLATFORM

The building of the ping-pong ball video game tactical analysis platform needs to match the algorithms mentioned above, and the relationship between each module is shown in Figure 5.

The camera module is responsible for acquiring the pictures taken, and at least two cameras are needed, ensuring that both cameras acquire the images meanwhile. The camera module plays the role of data transmission between the identification and detection module and the tracking module. The detection module receives the image data transmitted by the camera module, searches the pictures of the two viewpoints respectively, determines whether there is a target

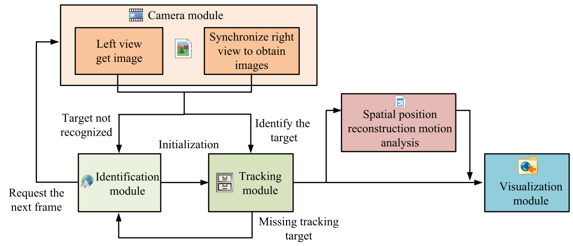


FIGURE 5. The relationship between modules.

object, and outputs the coordinates of the bounding box. If the target object is not found, the detection module requests the camera module to obtain the next frame of image. The tracking module receives the image data transmitted by the camera module and uses the bounding box coordinates output by the detection module as the initial value. The tracking algorithm constantly updates this value to output the predicted coordinates. If successfully tracked, the bounding box coordinates will be output. If the trace fails, the detection module is called for a global search to find the target. The module receives the coordinates of the bounding box output by the tracking module, analyzes the movement of ping-pong ball, and displays the results visually.

In the design of the ping-pong ball video game tactical analysis platform, 2 cameras are put on one side of the ping-pong ball table to simultaneously shoot the table area through the hardware trigger and prevent movement. Camera model specifications need to be consistent to ensure accurate calculation of 3D coordinates. After setting up the camera, it is necessary to calibrate the parameter matrix in the camera and ensure that the table is in the field of view of the camera. The tracking algorithm includes the recognition module to obtain the candidate region, exclude the candidate region that is far away from the previous frame position. The candidate regions are then entered into the CNN model and the probability values and bounding boxes for each region are obtained. Select the corresponding bounding box based on the probability value and return the average size of the bounding box. When the probability value is greater than the set threshold, the CNN output is considered reliable. When a single tracking fails, the next frame coordinate is selected as the tracking result; Or re-execute the first step of the frame to search for tracking targets throughout the graph. Tracking failures usually occur when the ping-pong ball flies out of view or away from the camera and have little effect on the work of the frame. It is currently not possible to integrate rotation information measurement into the tracking framework because the camera frame rate needs to be above 300FPS.

IV. EXPERIMENTAL ANALYSIS OF PING-PONG BALL VIDEO GAME TACTICAL ANALYSIS METHOD

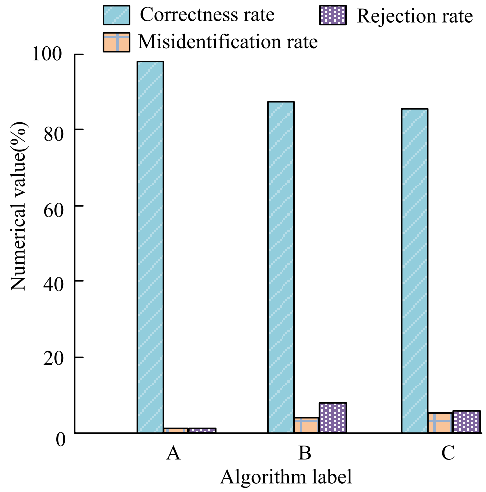
This section verifies the effect of the ping-pong ball video game tactical analysis method, and verifies the application effect of the ping-pong ball video game tactical analysis platform through the construction of the actual environment. Firstly, the effectiveness of the tactical analysis method for table tennis video games was verified by constructing a practical environment. Secondly, the effectiveness of the fuzzy edge recognition algorithm in table tennis image recognition was verified through comparison with other algorithms. Then, the effectiveness of the table tennis target tracking algorithm was verified by comparing it with the direct linear transformation algorithm and the Kalman filter tracking algorithm. Subsequently, the effectiveness of the spatial information estimation and trajectory prediction methods for table tennis was verified through comparison with computer-generated data and actual images. Finally, the effectiveness of the table tennis rotation measurement method was verified by comparing it with videos of different speeds.

A. EFFECT VERIFICATION OF FUZZY EDGE RECOGNITION ALGORITHM FOR PING-PONG IMAGES

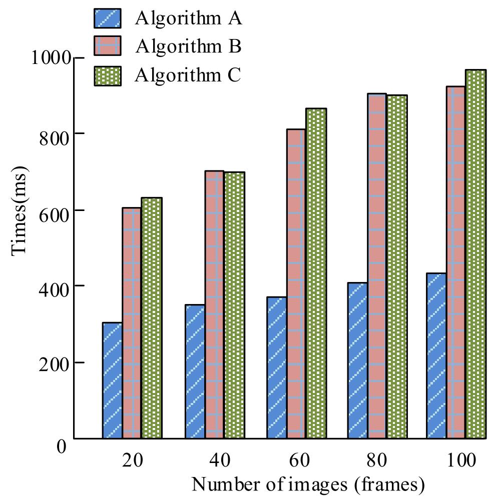
To verify the effect of the algorithm, the experiment takes Windows as the operating system, and the implementation language of the algorithm is Python. In this study, 1,400 ping-pong images were taken by camera, of which 1,000 were used for model training and 400 were used for model testing. In this paper, the effect of fuzzy edge recognition algorithm (marked as A) for ping-pong images is verified, and the image edge detection algorithm based on interval value self-blurred (marked as B) and image edge detection method based on morphology (marked as C) are compared. The comparative test results of the three recognition and detection algorithms are shown in Figure 6.

In Figure 6, the recognition accuracy of the fuzzy edge recognition algorithm proposed in the research is 98.1%, and the error and rejection rates are less than 1.6%. Compared with the other two algorithms, the proposed algorithm has better performance. In Figure 6 (b), as the number of images to be recognized increases, the algorithm recognition time also increases gradually. The fuzzy edge recognition algorithm proposed in this paper takes the least time among the three algorithms, and can be quickly recognized. Table 1 shows the anti-noise performance test results of different algorithms.

As can be seen from Table 1, the recognition errors of each algorithm gradually increase with the increase of noise intensity. In general, the error of the ping-pong ball image fuzzy edge recognition algorithm proposed in this paper is minimal. When the noise intensity is 0.35dB, the recognition error of the ping pong image fuzzy edge recognition algorithm is 0.35, which is 0.17 lower than that of the image edge detection algorithm based on interval value conscious fuzzy. Computational complexity is a concept that describes the time and spatial resources required by an algorithm during its execution. Time complexity is the worst-case time complexity of an algorithm, representing the relationship between the required execution time of the algorithm and the input size at the maximum input size. Spatial complexity is a concept that describes the spatial resources required by an algorithm



(a)Algorithm performance test results



(b)Algorithm recognition time comparison

FIGURE 6. Comparative test results of three recognition detection algorithms.

during execution, representing the relationship between the maximum space required by the algorithm during execution and the input size. When analyzing and comparing algorithm performance, it is necessary to comprehensively consider both time complexity and spatial complexity. The optimal performance of an algorithm usually refers to solving problems with the lowest possible computational complexity. To verify the computational complexity of the fuzzy edge recognition algorithm for table tennis images (marked as A), this study compares it with the image edge detection algorithm based on interval value conscious blur (marked as B) and the image edge detection method based on morphology (marked as C). The comparison of computational complexity of different recognition algorithms is shown in Figure 7.

Figure 7 (a) shows a comparison of the time complexity of recognition algorithms. It can be seen that the proposed fuzzy edge recognition algorithm for table tennis images has a linear order of time complexity, which is lower than the image

TABLE 1. Test results of anti noise performance of different algorithms(Identification error).

Algorithm label	Noise intensity(dB)									
	0.06	0.12	0.18	0.24	0.30	0.36	0.42	0.48	0.54	0.60
A	0.12	0.13	0.14	0.16	0.20	0.23	0.25	0.29	0.32	0.35
B	0.17	0.19	0.22	0.26	0.33	0.35	0.38	0.43	0.47	0.52
C	0.16	0.18	0.21	0.25	0.32	0.36	0.40	0.44	0.47	0.52

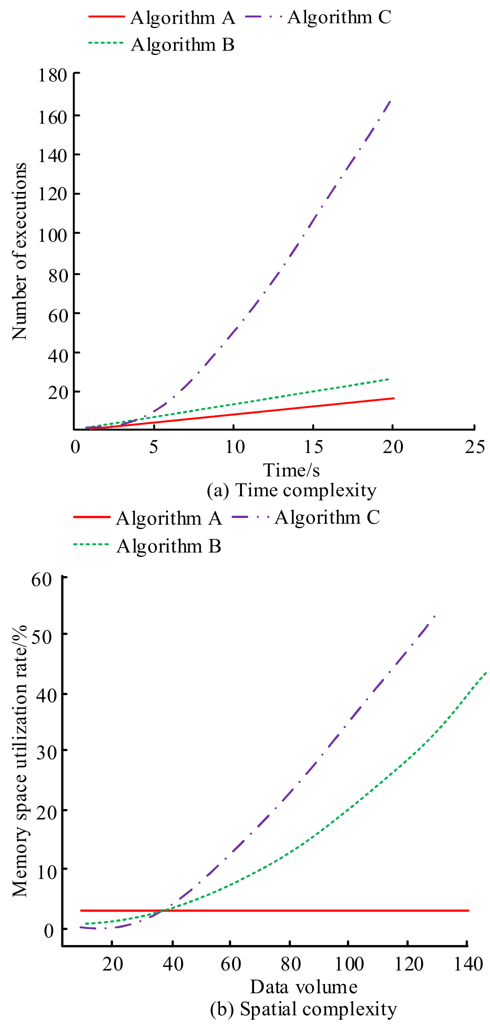


FIGURE 7. Comparison of computational complexity of different recognition algorithms.

edge detection algorithm based on interval value self blurring and the image edge detection method based on morphology. Figure 7 (b) shows a comparison of the spatial complexity of recognition algorithms. It can be seen that the spatial complexity of the proposed fuzzy edge recognition algorithm for table tennis images is a constant order, which is lower than that of the image edge detection algorithm based on interval value self blurring and the image edge detection method based on morphology. This indicates that the computational complexity of the fuzzy edge recognition algorithm for table tennis images is relatively low, and compared to the other two algorithms, it consumes less time and space.

B. PING-PONG TARGET TRACKING ALGORITHM EFFECT VERIFICATION

In the study, the learning rate of the lower layer of the network is set to 1 × 10.6, the weight attenuation is set to 10, the number of iterations of the classification stage is 5, and the attenuation coefficient of the learning rate is 0.1. In the training of the regression layer, the iterationsare4, and the training set uses positive samples containing only ping-pong ball. To analyze the performance of the ping-pong ball target tracking algorithm (labeled TTT), the classical visual geometry group network-16 is used as the basic network structure in this study. The performance of the algorithm is evaluated by training a new model, and the direct linear transformation (DLT) algorithm is compared with Kalman filter tracking. The comparison of success rate and accuracy rate of different methods is shown in Figure 8.

Figure 8 (a) shows the comparison of success rates of different methods. It can be seen that the success rate of each algorithm gradually decreases with the increase of overlap threshold. In contrast, the proposed ping-pong ball target tracking algorithm has a higher success rate, up to 93.4%. Figure 8 (b) shows the accuracy comparison of different algorithms. With the increase of positioning errors, the accuracy rate of the algorithm gradually increases. When the positioning error is 10%, the precision of the ping-pong ball target tracking algorithm can reach 94.3%, which is 9.3% higher than that of the direct linear transform algorithm.

C. PING-PONG SPATIAL INFORMATION ESTIMATION AND TRAJECTORY PREDICTION METHOD EFFECT VERIFICATION

To verify the effect of ping-pong ball spatial information estimation and trajectory prediction methods, this study uses computer-generated images and actual pictures to carry out comparison experiments. The actual shot data consisted of placing six ping-pong balls on a ball table and recording their actual coordinates. Computer generated images are modeled using Unity 3D, modeled to standard ping-pong balls and table sizes, and placed on the table in the same position as the actual data. The error of single-line-of-sight position estimation in computer-generated data is shown in Table 2.

In Table 2, the error is the Euclidean distance between the estimated coordinates and the actual coordinates. In the single view Angle, the average value of the coordinate error estimated in the computer-generated data is 2.5954mm, and the actual image error caused by the ping-pong ball spatial information estimation method is very small. The prediction results of the ping-pong ball motion trajectory prediction model are shown in Figure 9.

In Figure 9, when the input coordinates are 4, the average error is 181.94mm, and the ideal average error is 162.60mm. When the input coordinates are 30, the average error is

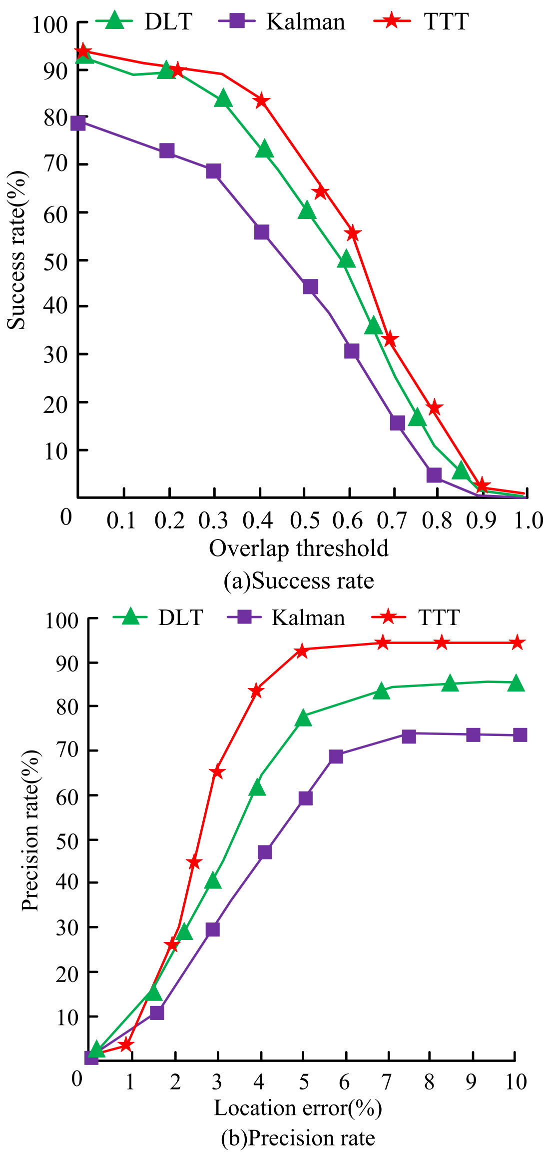


FIGURE 8. Comparison of success rate and accuracy of different methods.

36.46mm, and the ideal average error is 33.65mm. The results show that when the input coordinates increase, the predicted trajectory approaches to the target value. MDN predicts the internal state of ping-pong ball rebound, as shown in Figure 10.

In Figure 10, the MDN model can predict the downward movement of the ping-pong ball before the rebound; After the rebound, the model was able to predict the ball's upward movement and assign higher weights to situations with higher speeds. This shows that MDN model has a good performance in learning and predicting the motion behavior of objects.

D. EFFECT VERIFICATION OF PING-PONG BALL ROTATION MEASUREMENT METHOD

In ping-pong ball rotation measurement experiment, the research carried out rotation speed measurement on different speed videos. The speed results obtained by video calculation of different speed are shown in Figure 11.

TABLE 2. Error in estimating the position of a single line of sight point in computer-generated data.

Number	Estimated coordinates(mm)			Actual coordinates(mm)			Error(mm)
	X	Y	Z	X	Y	Z	
1	481.39	458.88	19.03	480	457	20	2.5304
2	1018.13	454.69	21.28	1020	457	20	3.2357
3	719.23	910.46	19.02	720	912	20	1.9823
4	478.87	2282.67	172.89	480	2284	170	2.5158
5	1018.99	1828.49	168.01	1020	1827	170	2.6833
6	718.22	2285.03	171.54	720	2284	170	2.5876
7	482.01	1356.03	211.02	480	1355	210	2.4787
8	1018.02	2650.31	208.88	1020	2651	210	2.0982
9	717.01	2433.78	210.18	720	2435	210	3.2465

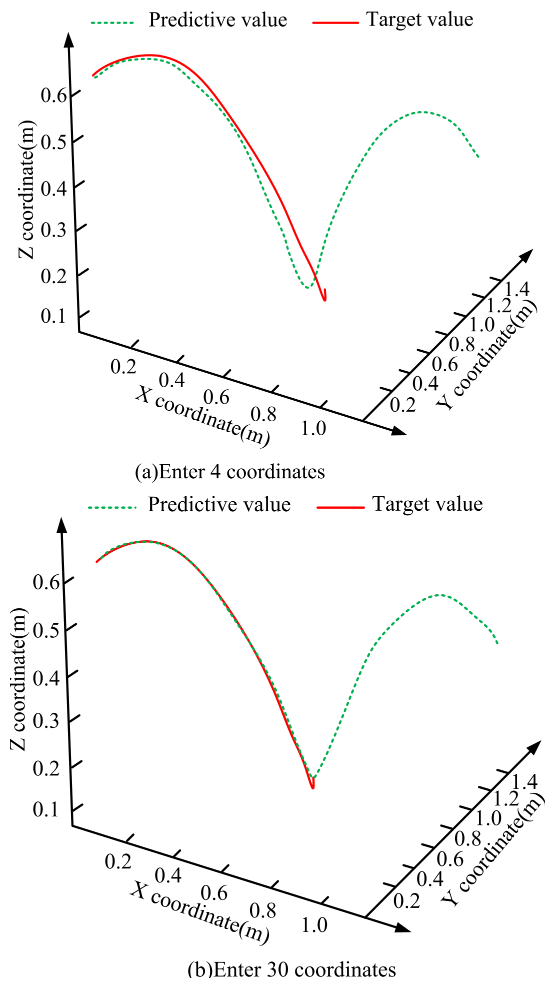


FIGURE 9. The prediction results of the ping-pong ball trajectory prediction model.

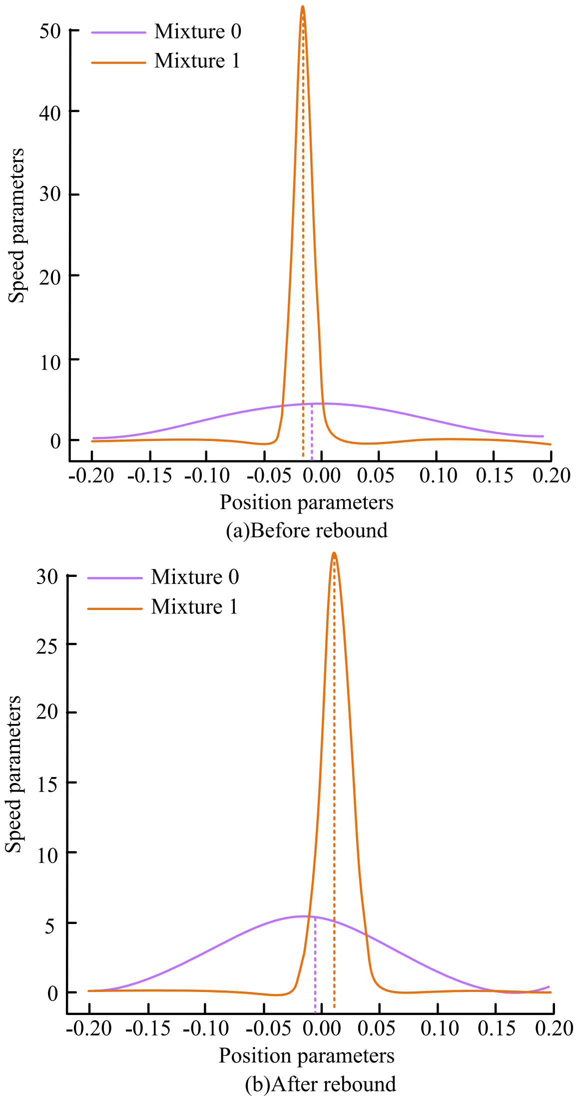


FIGURE 10. The prediction results of the ping-pong ball trajectory prediction model.

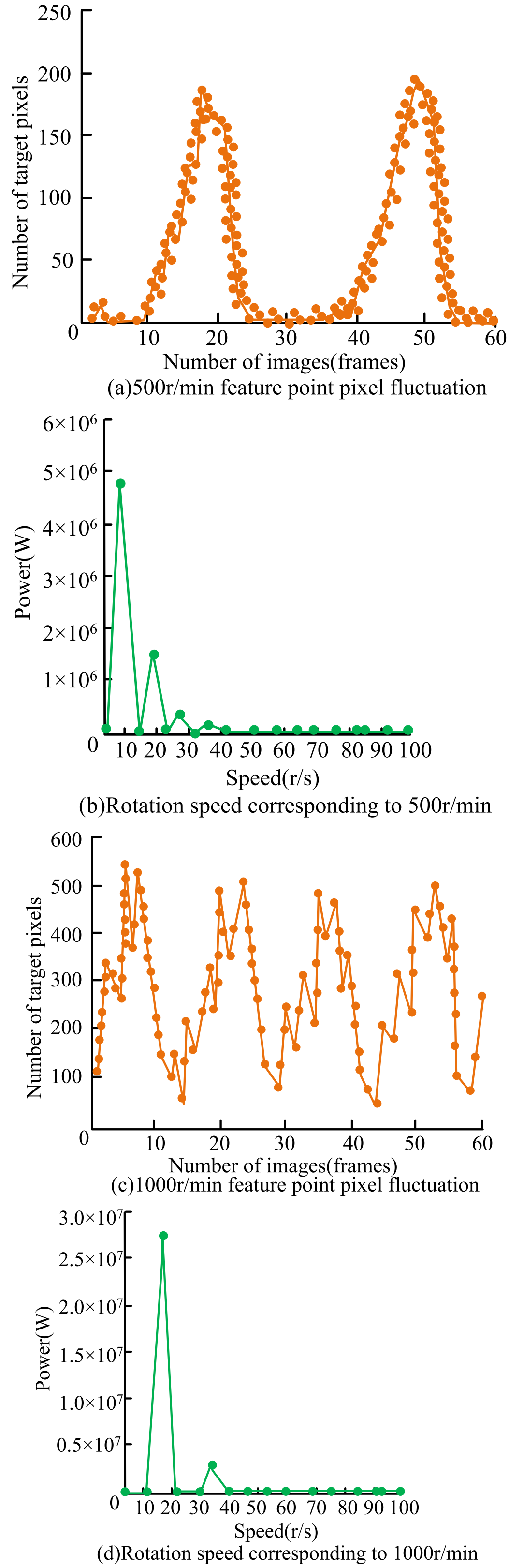


FIGURE 11. Speed results calculated from videos with different speeds.

In Figure11, the speed results corresponding to different speed videos can be estimated by observing the highest response frequency in the frequency response graph. A higher response frequency usually corresponds to a higher speed, while a lower response frequency usually corresponds to a lower speed. The speed measurement results of different ping-pong ball speed videos are shown in Table 3.

In Table 3, the error of speed measurement results of different ping-pong ball speed videos is less than 0.5r/s, and the error ratio is less than 2%. This indicates that the error is relatively small compared with the measurement results, and will not have a large impact on the measurement results.To further validate the effectiveness of the proposed method, the study will use different datasets and methods to compare and analyze the effectiveness of trajectory prediction and rotation measurement methods. The comparison results of trajectory prediction and rotation measurement methods in different datasets are shown in Table 4.

TABLE 3. Comparison of speed measurement results for different ping-pong ball speed videos.

Serial number	True speed(r/s)	Measured speed(r/s)	Absolute error(r/s)	Error proportion(%)
1	8.000	8.021	0.021	0.26%
2	8.333	8.474	0.141	1.66%
3	16.000	16.034	0.034	0.21%
4	16.666	16.795	0.129	0.77%
5	25.000	25.432	0.432	1.70%
6	25.500	25.614	0.114	0.45%
7	30.000	29.662	0.338	1.14%

TABLE 4. Comparison results of trajectory prediction and rotation measurement methods in different data-sets.

Data-set name	Method classification	Method name	Accuracy	Operability	Cost performance
ITTF World Championships Data-set [26]	Trajectory prediction	Proposed	93.6%	91.2%	95.1%
		Visual estimation	89.3%	90.5%	86.3%
		Physical model estimation	83.2%	85.1%	84.1%
TUM-Ping--Pong Data-set [27]	Rotation measurement	Proposed	98.2%	95.3%	96.7%
		Manual counting method	80.1%	80.4%	75.6%
		High speed camera method	99.6%	82.6%	78.1%

As shown in Table 4, in the ITTF World Championships Data-set, compared to the Visual estimation and Physical model estimation methods, the proposed trajectory prediction method has the highest accuracy, operability, and cost-effectiveness scores, with 93.6%, 91.2%, and 95.1%, respectively. This indicates that the trajectory prediction method proposed in the ITTF World Championships Data-set has high accuracy and operability, as well as good cost-effectiveness. In the TUM Ping-Pong Data-set, compared to the Manual counting method and High speed camera method, the proposed trajectory prediction method for table tennis rotation measurement has the highest operability and cost-effectiveness scores, with 95.3% and 96.7%, respectively. This indicates that the rotation measurement method proposed in the TUM Ping-PongData-set also has high operability and cost-effectiveness. To gain a more comprehensive understanding of the model's generalization ability, experiments were conducted using different datasets to analyze the accuracy, recall, and F1 values of the research methods. The performance parameters of the proposed methods under different datasets are compared in Table 5.

In Table 5, the edge recognition, target tracking, and trajectory prediction methods proposed in the study performed the best in the Table Tennis Video Data-set. However, the performance difference of rotation measurement methods in the three datasets is not significant. Overall, the impact of different datasets on the performance of the research method is not significant, indicating that the research method has good universality and generalization ability.

TABLE 5. The performance parameters of the proposed methods under different data-sets.

Method name	Data-set name	Accuracy	Recall	F1 value
Edge recognition	ITTF World Championships Data-set	94.5%	93.5%	94.2%
	TUM-Ping-Pong Data-set	95.2%	95.7%	95.1%
	Table Tennis Video Data-set [28]	96.3%	97.3%	96.2%
Target tracking	ITTF World Championships Data-set	95.7%	96.7%	95.6%
	TUM-Ping-Pong Data-set	96.3%	97.3%	96.8%
	Table Tennis Video Data-set	97.8%	96.7%	97.1%
Trajectory prediction	ITTF World Championships Data-set	93.6%	92.5%	92.4%
	TUM-Ping-Pong Data-set	94.5%	93.7%	93.9%
	Table Tennis Video Data-set	96.7%	98.4%	97.2%
Rotation measurement	ITTF World Championships Data-set	98.2%	97.3%	96.5%
	TUM-Ping-Pong Data-set	98.1%	97.5%	96.4%
	Table Tennis Video Data-set	98.6%	97.6%	96.8%

E. APPLICATION EFFECT OF PING-PONG BALL VIDEO GAME TACTICAL ANALYSIS PLATFORM

The research used C++ to build a table tennis video tactical analysis platform, combined with Qt to write a graphical interface, and implemented RNN and LSTM models using Caffe and Tensorflow. The current version number of the platform is 1.0, and the operating system is Windows 10. The hardware and software requirements include at least 4 cores of CPU, 4GB of memory, 256GB of SSD storage space, etc. The programming language used by the platform is Python, and the algorithms include machine learning, deep learning, etc. The data structures include hash tables, lists, etc. The platform tracking performance test results are shown in Figure 12.

In Figure 12, the tracking frame can record the trajectory of the ping-pong ball more completely and make accurate trajectory prediction. The results show that the tracking performance test of the ping-pong ball video game tactical analysis platform is good. The tactical indicators generated by the ping-pong ball video game tactical analysis platform are shown in Figure 13.

In Figure 13, the ping-pong ball video game tactical analysis platform can analyze the speed of ping-pong ball and calculate thedroppointof ping-pong ball according to the video. Players can learn about their own and their opponents'

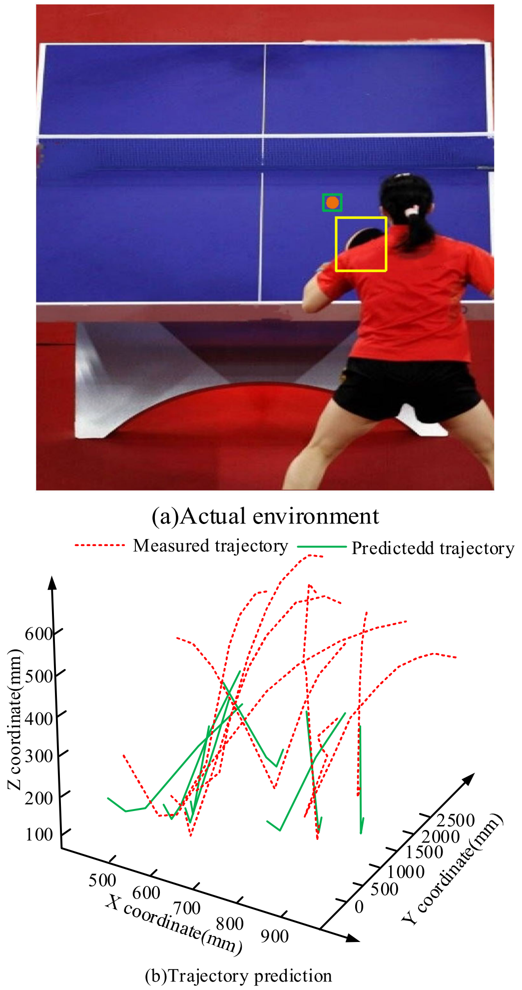


FIGURE 12. **Platform tracking performance test results.**

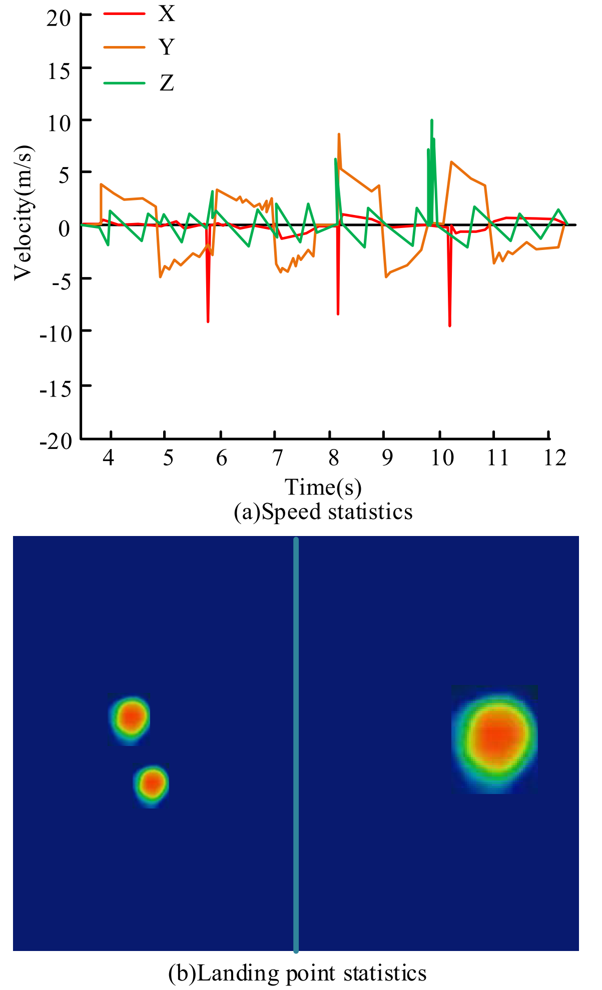


FIGURE 13. **The tactical indicators generated by the ping-pong ball video tactical analysis platform.**

hitting habits and technical levels, so as to develop more effective tactical strategies. The real-time requirements of table tennis video analysis methods are high because table tennis matches are fast and require fast and accurate analysis of ball trajectory, speed, and other information. Generally speaking, the overall delay should be controlled within 100 ms as much as possible to ensure the real-time and accuracy of the analysis results.Research will be conducted to apply the table tennis video tactical analysis platform to real-time matches to verify its responsiveness. The real-time time analysis results of the table tennis video tactical analysis platform are shown in Table 6.

In Table 6, When the ping-pong video tactical analysis platform is applied to the real-time match field, its real-time prime analysis results show that the time delay of each algorithm is less than 30 ms, and the overall time delay is less than 100 ms. This indicates that the platform has high real-time performance and can meet the real-time analysis needs of table tennis matches on the field. The real-time time analysis results of this platform indicate that it can perform real-time analysis on the real-time data flow of table

TABLE 6. **Real time analysis results of table tennis video tactical analysis platform.**

Serial number	Edge detection	Target tracking	Trajectory prediction	Rotation measurement
1	23 ms	26 ms	14 ms	21 ms
2	14 ms	15 ms	23 ms	24 ms
3	21 ms	12 ms	17 ms	15 ms
4	19 ms	14 ms	25 ms	24 ms
5	21 ms	19 ms	23 ms	15 ms

tennis matches and display the analysis results in real time. This provides important reference information for table tennis players, which can help them adjust their tactics in a timely manner during the competition and improve their performance. From an industrial perspective, the application of a table tennis video tactical analysis platform can help improve the real-time and accuracy of analysis on the table tennis field, thereby improving the competitive level and performance of athletes. In addition, the platform can provide important data support for the development of table tennis, providing better training and competition conditions for athletes and coaches.

V. CONCLUSION

Aiming at the tactical analysis of ping-pong ball video skills, this research proposes an algorithm based on image fuzzy edge recognition. The algorithm tracks and detects ping-pong balls by simplifying the structure of neural network, and builds the corresponding analysis platform by combining the method of spatial position of single-view ping-pong balls. The recognition accuracy of this algorithm is 98.1%, and the error rate and rejection rate are less than 1.6%. Compared with the image edge detection algorithm based on interval value conscious fuzzy, the image edge recognition algorithm based on fuzzy image has better performance. When the noise intensity is 0.35dB, the recognition error of the ping- pong image fuzzy edge recognition algorithm is 0.35, which is 0.17 lower than that of the image edge detection algorithm based on interval value conscious fuzzy, the average recognition error decreased by 32.7%. In addition, the precision of the ping-pong ball target tracking algorithm can reach 94.3% when the positioning error is 10%. Compared with the direct linear transformation algorithm, the accuracy is improved by 9.3%. When the input coordinates are 4, the average error of trajectory prediction is 181.94mm, and the ideal average error is 162.60mm. When the input coordinates are 30, the average error of trajectory prediction is 36.46mm and the ideal average error is 33.65mm. The results show that when the input coordinates rise, the predicted trajectory approaches to the target value. The ping-pong ball video game tactical analysis platform can analyze the speed of ping-pong ball according to the video, and statistics the droppointof ping-pong ball, so as to help players develop more effective tactics and strategies to improve their competitive level and achievements. The limitation of this study is that camera calibration typically requires a large amount of image data and complex algorithms for computation, thus consuming a significant amount of memory and processor resources. In terms of calibration time, it depends on the complexity of the calibration method and algorithm used, as well as the number of images processed. For complex camera calibration algorithms, it may take several hours or even longer to complete the calibration process. Future research can simplify the calibration process of single view cameras and improve the accuracy of spatial coordinate estimation by improving computational efficiency and optimizing algorithms. In addition, it is also possible to consider using multi view camera calibration technology, which can improve calibration accuracy and robustness by simultaneously calibrating multiple cameras. Specifically, researchers can explore and implement more efficient computing methods and algorithms such as parallel computing and GPU acceleration to reduce computation time and resource consumption. At the same time, design a more simplified calibration process, simplify the calibration process through automated calibration processes and automatic feature point extraction methods. In addition, by using more accurate camera models and more accurate feature point matching algorithms, calibration accuracy and precision can be improved. In addition, consider using multi view camera calibration technology to further improve calibration accuracy and robustness by simultaneously calibrating multiple cameras.

REFERENCES

[1] X. Yu, ''Evaluation of training efficiency of table tennis players based on computer video processing technology,'' *Optik*, vol. 273, Feb. 2023, Art. no. 170404, doi: 10.1016/j.ijleo.2022.170404.

[2] C. He, X. Zhang, Y. Gui, Y. Liu, and W. Zhang, ''Mathematical modeling and simulation of table tennis trajectory based on digital video image processing,'' *Adv. Math. Phys.*, vol. 2021, no. 1, Dec. 2021, Art. no. 7045445, doi: 10.1155/2021/7045445.

[3] R. Qi and R. Li, ''Network multimedia table tennis teaching design based on embedded microprocessor,'' *Wireless Commun. Mobile Comput.*, vol. 2022, no. 1, Jan. 2022, Art. no. 2019857, doi: 10.1155/2022/2019857.

[4] K. Firdaus and D. T. Mario, ''Development of service sensor tools on table tennis net,'' *J. Phys. Educ. Sport*, vol. 22, no. 6, pp. 1449–1456, Jun. 2022, doi: 10.7752/jpes.2022.06182.

[5] H. Li, S. G. Ali, J. Zhang, B. Sheng, P. Li, Y. Jung, J. Wang, P. Yang, P. Lu, K. Muhammad, and L. Mao, ''Video-based table tennis tracking and trajectory prediction using convolutional neural networks,'' *Fractals*, vol. 30, no. 5, Aug. 2022, Art. no. 2240156, doi: 10.1142/s0218348x22401569.

[6] C. Chen, B. Liu, F. Song, J. Jiang, Z. Li, C. Song, J. Li, G. Jin, and J. Wu, ''An adaptive fuzzy logic control of green tea fixation process based on image processing technology,'' *Biosyst. Eng.*, vol. 215, pp. 1–20, Mar. 2022, doi: 10.1016/j.biosystemseng.2021.12.023.

[7] B. E. Schmidt and M. R. Woike, ''Wavelet-based optical flow analysis for background-oriented Schlieren image processing,'' *AIAA J.*, vol. 59, no. 8, pp. 3209–3216, Feb. 2021, doi: 10.31219/osf.io/m6g4u.

[8] J. Chen, D. Zhang, S. Yang, and Y. A. Nanehkaran, ''Intelligent monitoring method of water quality based on image processing and RVFL-GMDH model,'' *IET Image Process.*, vol. 14, no. 17, pp. 4646–4656, Feb. 2021, doi: 10.1049/iet-ipr.2020.0254.

[9] D. Zhou, G. He, K. Xu, and C. Liu, ''A two-stage hue-preserving and saturation improvement color image enhancement algorithm without gamut problem,'' *IET Image Process.*, vol. 17, no. 1, pp. 24–31, Sep. 2022, doi: 10.1049/ipr2.12613.

[10] Z. Wang, F. He, H. Zhang, P. Hao, X. Zhang, and X. Li, ''Three-dimensional measurement of the droplets out of focus in shadowgraphy systems via deep learning-based image-processing method,'' *Phys. Fluids*, vol. 34, no. 7, Jul. 2022, Art. no. 073301, doi: 10.1063/5.0097375.

[11] F. Qiao, ''Application of deep learning in automatic detection of technical and tactical indicators of table tennis,'' *PLoS One*, vol. 16, no. 3, Mar. 2021, Art. no. e0245259, doi: 10.1371/journal.pone.0245259.

[12] H. Zhao and F. Hao, ''Target tracking algorithm for table tennis using machine vision,'' *J. Healthcare Eng.*, vol. 2021, no. 1, May 2021, Art. no. 9961978, doi: 10.1155/2021/9961978.

[13] L. Yang, H. Zhang, X. Zhu, and X. Sheng, ''Ball motion control in the table tennis robot system using time-series deep reinforcement learning,'' *IEEE Access*, vol. 9, pp. 99816–99827, 2021, doi: 10.1109/ACCESS.2021.3093340.

[14] W. Li, ''Analyzing the rotation trajectory in table tennis using deep learning,'' *Soft Comput.*, vol. 27, no. 17, pp. 12769–12785, Jul. 2023, doi: 10.1007/s00500-023-08962-8.

[15] I. Malagoli Lanzoni, S. Bartolomei, R. Di Michele, Y. Gu, J. S. Baker, S. Fantozzi, and M. Cortesi, ''Kinematic analysis of the racket position during the table tennis top spin forehand stroke,'' *Appl. Sci.*, vol. 11, no. 11, p. 5178, Jun. 2021, doi: 10.3390/app11115178.

[16] Y. Ji, Y. Mao, F. Suo, X. Hu, Y. Hou, and Y. Yuan, ''Opponent hitting behavior prediction and ball location control for a table tennis robot,'' *Biomimetics*, vol. 8, no. 2, p. 229, May 2023, doi: 10.3390/biomimetics8020229.

[17] S. Zhou, X. Sui, W. Zhang, Y. Hua, Q. Chen, and G. Gu, ''High-resolution image transmission through scattering media based on compressive encoding,'' *Opt. Eng.*, vol. 60, no. 3, Mar. 2021, Art. no. 035108, doi: 10.1117/1.oe.60.3.035108.

[18] H. Li and W. Chen, "RIP based condition for support recovery with A* OMP in the presence of noise," *IET Signal Process.*, vol. 14, no. 5, pp. 307–313, Jul. 2020, doi: 10.1049/iet-spr.2019.0478.

[19] C. Zhang, Q. Chen, M. Wang, and S. Wei, "Optimised two-dimensional orthogonal matching pursuit algorithm via singular value decomposition," *IET Signal Process.*, vol. 14, no. 10, pp. 717–724, Feb. 2021, doi: 10.1049/iet-spr.2019.0090.

[20] C. Zhang, Z. Feng, Z. Gao, X. Jin, D. Yan, and L. Yi, "Salient feature multimodal image fusion with a joint sparse model and multiscale dictionary learning," *Opt. Eng.*, vol. 59, no. 5, p. 1, Dec. 2019, doi: 10.1117/1.oe.59.5.051402.

[21] A. Filatov and K. Krinkin, "A simplistic approach for lightweight multi-agent SLAM algorithm," *Int. J. Embedded Real-Time Commun. Syst.*, vol. 11, no. 3, pp. 67–83, Jul. 2020, doi: 10.4018/ijertcs.2020070104.

[22] L. Xu, H. Yin, T. Shi, D. Jiang, and B. Huang, "EPLF-VINS: Real-time monocular visual-inertial SLAM with efficient point-line flow features," *IEEE Robot. Autom. Lett.*, vol. 8, no. 2, pp. 752–759, Feb. 2023, doi: 10.1109/LRA.2022.3231983.

[23] P. Burgholzer, G. Mayr, G. Thummerer, and M. Haltmeier, "Heat diffusion blurs photothermal images with increasing depth," *J. Appl. Phys.*, vol. 131, no. 21, Jun. 2022, Art. no. 211101, doi: 10.1063/5.0093315.

[24] Y. Guo, Z. Mustafaoglu, and D. Koundal, "Spam detection using bidirectional transformers and machine learning classifier algorithms," *J. Comput. Cognit. Eng.*, vol. 2, no. 1, pp. 5–9, Apr. 2022, doi: 10.47852/bonviewjcce2202192.

[25] P. A. Ejegwa and J. M. Agbetayo, "Similarity-distance decision-making technique and its applications via intuitionistic fuzzy pairs," *J. Comput. Cognit. Eng.*, vol. 2, no. 1, pp. 68–74, Jan. 2022, doi: 10.47852/bonviewjcce512522514.

[26] J. Lennartz, A. Groll, and H. van der Wurp, "Predicting table tennis tournaments: A comparison of statistical modelling techniques," *Int. J. Racket Sports Sci.*, vol. 3, pp. 39–48, Dec. 2021, doi: 10.30827/digibug.73877.

[27] S. S. Tabrizi, S. Pashazadeh, and V. Javani, "Comparative study of table tennis forehand strokes classification using deep learning and SVM," *IEEE Sensors J.*, vol. 20, no. 22, pp. 13552–13561, Nov. 2020, doi: 10.1109/JSEN.2020.3005443.

[28] K. Aktas, M. Demirel, M. Moor, J. Olesk, C. Ozcinar, and G. Anbarjafari, "Spatiotemporal based table tennis stroke-type assessment," *Signal, Image Video Process.*, vol. 15, no. 7, pp. 1593–1600, Mar. 2021, doi: 10.1007/s11760-021-01893-7.

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