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PREDICTION OF THE BEST HIT POINT OF TENNIS SERVE BASED ON MEAN SHIFT ALGORITHM

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Abstract: The prediction accuracy of traditional tennis serve best hitting point prediction method is greatly affected by external factors such as the complexity of the environment, resulting in low prediction accuracy and efficiency. To address the above problems, the best hitting point prediction method of tennis serve based on the Mean Shift algorithm is studied. After acquiring and processing the video image of tennis serve, we detect the moving object in the image and track the tennis ball movement in the image by using the Mean Shift algorithm. Finally, the Kalman filter is used to predict the best hitting point of the serve. The experimental results demonstrate that the studied prediction method is efficient, improves the prediction accuracy by at least 50% on average, and can be applied in practice to improve the training effect of athletes.

Keywords: Mean Shift algorithm; tennis serve; hitting point of serve; optimal hitting point prediction; Kalman filtering.

0 Introduction

The tennis hitting point position is the main factor affecting the quality of the player's serve. The tennis hitting point positioning is important for the player to find the best hitting point position, improve his ability to predict the best hitting point position and even improve the tennis technique. The tennis hitting point is the point in time and space where the racket makes contact with the ball when the player hits the ball. Only by finding the best hitting point can one make the most advantageous and accurate strike at the moment of hitting the ball. The optimal hitting point helps to maximize the efficiency of the hitting action. In tennis, serve technique is the key to scoring a winning point and is a difficult area in training. In the traditional training model, the coach first demonstrates and explains, the player practices the action in the court according to his own understanding, and then the coach gives individual and targeted instruction to correct the mistakes made in the serve. In this teaching mode, players do not have a correct comparison standard, and it is difficult to recognize their mistakes fundamentally, which is not conducive to their mastery of serve technique. Through the integration of advanced science and technology, modern tennis training techniques have been improved, and many use computer technology to analyze player data thus improving training efficiency [1].

The popularity of contemporary tennis training techniques, the application of computer applications, video image processing and artificial intelligence technologies in the tennis training context has led to the rapid development of tennis training optimization theory and practice. Vision is the most direct sense for human to perceive the environment, and the main way for human to

know the external information is through vision. With the continuous improvement of computer performance, the rapid development of computer vision and the rapid progress of information technology, so that scientific and modern training techniques are widely used in tennis. Computer vision processing technology for sports analysis plays an important role in sports such as competitive sports and skillful sports. Because it can do without any interference to the athletes through the camera device to obtain accurate and comprehensive sports data, further analysis of the athletes' technical movements, help coaches and athletes to find irregularities or errors, improve the efficiency of sports training, improve sports technology, and thus achieve the purpose of supporting training.

The method of predicting the best hitting point of tennis serve mentioned in the literature [2] uses the principle of analyzing the force on the tennis ball to determine the trajectory of the tennis ball in the air to achieve prediction. However, this prediction method ignores the influence of the tennis ball's rotation on the tennis ball's flight trajectory caused by the tennis player's serve position and force mode, which leads to the unstable accuracy of the prediction results. The 3D modeling method using image processing technology mentioned in the literature [3] predicts the best hitting point of tennis serve, and although this method has high accuracy, its processing accuracy depends largely on the accuracy of hardware equipment, and the cost is high when it is actually used. When the hitting point prediction method based on the improved fast difference algorithm mentioned in the literature [4] is applied to complex environmental scenes, its prediction effect is disturbed by the light and background elements in the environment, which leads to a large error in predicting the best hitting point and affects the training effect of athletes.

Mean Shift algorithm, or mean drift algorithm, is a density-based nonparametric clustering algorithm. The algorithm finds the direction in which any sample point increases in density the fastest after clustering by setting the principle that data sets of different cluster classes conform to different probability density distributions. The data sample points corresponding to regions with high sample density eventually form the data set with maximum local density and data convergence occurs at the location with maximum local density, and all points converging to the same local density maximum are considered as members of the same cluster class [5-6].Mean Shift is widely used in the field of computer vision and has good performance. Therefore, applying the Mean Shift algorithm to the daily training of tennis players, combined with camera equipment can find the best hitting point quickly and accurately without disturbing the training status of the players, thus improving the training quality, helping the players to master the action skills better and improving the training efficiency. Based on the above analysis, this paper will study the method of predicting the best hitting point of tennis serve based on Mean Shift algorithm and verify the effectiveness of the method.

1 Research on the best hitting point prediction method for tennis serve based on the Mean Shift algorithm

1.1 Tennis serve action video image acquisition and processing

1.1.1 Tennis serve action video image capture

In this paper, a high-speed camera is used to capture the player's serve, stroke and tennis ball flight path. During the video image acquisition, the players are made to wear dark colors in order to facilitate tennis ball color feature extraction. The purpose of the high-speed camera invention is to turn invisibility into visibility. Human eye visual activity is inert with a threshold value of 24 times/second, i.e., images above this frequency we consider as continuous motion rather than still images. Therefore, from the point of view of moving image reproduction, the refresh frequency of the picture must be above 24Hz. Considering the rapidity and transient nature of tennis serves, this paper uses a short time capture and storage recording system to capture video images of tennis serves, which consists of: IOI Flare 2M360CCL camera, capture card, cable, PC computer and capture software. The IOI Flare 2M360CCL camera uses two high-speed CMOS models, with a choice of 2 and 4 megapixel resolutions, and a Camera Link interface and a CXP interface[7]. The detailed parameters are shown in Table 1 .

Table 1 High-speed camera parameters

Maximum resolution	The biggest frame rate	Pixel depth	Pixel size	Image type	Data output type	Overall dimensions
2048×1088pixels	340fps	8bit/10bit	5.5μm×5.5μm	Mono/Color	Camera Link Base, Medium, Full	63.5×63.5×44.1 mm

The Flare 2M360CCL camera features high frame rate acquisition, two selectable high resolutions, 8bit/10bit pixel depth, high dynamic range shooting, and support for RIO function to increase camera frame rate. The lens is Myrutron HS2541J, which features high resolution, large aperture and high stability, with a minimum working distance of 300mm, a focal length of 25mm and a field of view of 15° x 19°. After the high-speed camera captures the tennis serve video image, the tennis serve video is stored in the computer through the capture card, and the image is processed in the computer.

1.1.2 Tennis serve action video image pre-processing

Moving targets have rich information in the images, such as the player serving the ball, the ball hit out, etc., and all these rich information cannot be provided by a single image. Therefore, motion target detection is required by analyzing a series of images. The principle of motion target detection technique is to detect and extract foreground objects from the background in the image sequence by using techniques such as digital signal processing, and then further analyze and process the motion targets into small independent targets by using image features.

The commonly used value filtering only considers the pixel points within the current window and does not start from the image as a whole, which can easily change the true value of the image pixel points and cause the loss of effective image information. Therefore, this paper selects wavelet denoising method for video image denoising processing. A wavelet is constructed by a function

$\varphi(x)$ defined in a finite region, and when its Fourier transform makes the function $\varphi(x)$ satisfy the permissible conditions shown in the following equation, the function is called the mother wavelet, or called the fundamental wavelet [8].

$$C_{\varphi} = \int_{R} \frac{\varphi(\omega)}{\omega} d\omega < \infty \quad (1)$$

A series of wavelet functions obtained by stretching and shifting the basic wavelet functions are called a set of wavelet basis functions, as shown in the following formula.

$$\varphi_{a,b}(x) = \left| \frac{1}{\sqrt{a}} \right| \varphi\left(\frac{x-b}{a} \right) \quad (2)$$

In formula (2), the parameter a is used to control scaling, which reflects the width of a specific basis function; The parameter b is used to shift the function, and it determines how far the function is shifted along the X-axis. Therefore, for an arbitrary function $f(x) \in L^2(R)$, its continuous wavelet transform can be defined by the following formula [9-10] :

$$W_{a,b}(x) = \langle f, \varphi_{a,b} \rangle = \int_{-\infty}^{+\infty} f(x) \frac{1}{\sqrt{a}} \varphi\left(\frac{x-b}{a} \right) dx \quad (3)$$

In formula (3), $W_{a,b}(x)$ is the convolution of function $f(x)$ and $\varphi_{a,b}(x)$, which is the inner product of the two. From the definition of continuous wavelet transform, we can see that when the value of a is large, $W_{a,b}(x)$ will be stretched; Conversely, when a is smaller, $W_{a,b}(x)$ is compressed accordingly, so the parameter a is a scaling factor that can be used to control the shape of the wavelet function.

According to Heisenberg principle, the resolution of wavelet in frequency domain can also be controlled by parameter a. The larger a is, the higher the frequency domain resolution is, so we can increase the value of a to see the frequency details of the signal. On the contrary, the smaller a is, the higher the temporal resolution will be, which means that the wavelet transform has a higher frequency resolution and a lower temporal resolution in the low frequency part, and the opposite in the high frequency part, namely, a lower frequency resolution and a higher temporal resolution.

In practical application, two parameters of wavelet transform must be discretized, and the expression of discrete wavelet transform can be obtained according to the following formula [11].

$$\varphi_{j,k}(t) = \frac{1}{\sqrt{a_0^j}} \varphi\left(\frac{t - kb_0 a_0^j}{a_0^j} \right) = a_0^{-j/2} \varphi\left(a_0^{-j} t - kb_0 \right) \quad (4)$$

In formula (4), a_0^j is the unit expansion step length greater than 1; b_0 is a positive real number; j, k are both integers. Therefore, when using the discrete wavelet shown in the above equation to perform the discrete transform of a one-dimensional signal sequence, only the wavelet coefficients need to be processed appropriately and finally the wavelet inverse transform (reconstruction) can be performed to achieve the denoising. The wavelet decomposition and reconstruction process of

two-dimensional images can be extended on the basis of the decomposition and reconstruction algorithm of one-dimensional signals. The process is as follows: two filters, a high-pass filter and a low-pass filter, are used to filter the original image according to columns, and then two-takes-one sampling is performed to obtain two sub-images of size N×N/2. Then the two sub-images are filtered and sampled again using low-pass and high-pass, and four sub-images of size N/2×N/2 are obtained, so that the image completes a layer of wavelet decomposition. Then wavelet decomposition is performed on the sub-images again, and it stops after repeating a certain number of times according to the video size, and then image reconstruction processing is performed to complete the denoising process of the image. After the video image acquisition and processing of tennis serve action, the motion object in the image is detected.

1.2 Detection of moving objects in images

In order to reduce the computational effort, this paper uses an algorithm based on the first-order parametric inter-frame difference vector to detect fast moving targets in dynamic image sequences. The algorithm of inter-frame difference vector first-order parametric is used to perform the difference operation using the corresponding pixels of two or three consecutive frames when the gray level changes slightly in the image sequence, and if the change of pixel value at a point of the difference image is higher than the threshold, the region of this point is considered to be caused by the motion of the target; if the change of pixel value at a point of the difference image is lower than the threshold, the region of this point is considered to be the background in the image sequence. The motion region of the target in the video is calibrated and then these calibrations are used to target the location where the video target is located. The invalid information between frames of the image sequence data can be removed by using inter-frame differencing directly or indirectly to obtain change monitoring targets. In order to detect a valid moving target, the two-frame differencing method needs to satisfy the following conditions: the target should have a speed of motion, the background scene is stationary while its gray value changes are small, other interference noise is small and the change of the target's gray value is relatively large. These factors can affect the effect of two-frame difference method images to different degrees due to noise effects, background brightness, etc. [12-14].

If the video image sequence of tennis service motion after discrete wavelet denoising is $\left\{E\left(x_i, y_j, t_k\right), i, j = 0,1,\ldots,N-1, k = 0,1,\cdots,K\right\}$,which represents the gray value of point $\left(x_i, y_j\right)$ in the image plane at time t_k . The partial derivative vector formed by the partial derivatives of the gray function E defined by the difference between frames on the directions of X axis, Y axis and T axis is denoted as $\left[\frac{\partial E_{ij}}{\partial x}, \frac{\partial E_{ij}}{\partial y}, \frac{\partial E_{ij}}{\partial t}\right]$. Due to the movement of the target, the grayscale value of the target position changes dramatically. Therefore, the first norm of partial derivative vector can be used to judge the position of the drastic change of grayscale, so as to determine the tennis ball movement in the image. The formula is as follows:

$$D(i,j,t)=\left|\frac{\partial E_{ij}}{\partial x}\right|+\left|\frac{\partial E_{ij}}{\partial y}\right|+\left|\frac{\partial E_{ij}}{\partial t}\right| \quad (5)$$

When judging moving objects, only pixels with a large change in gray level, namely pixels with a large value of $D(i,j,t)$, should be tracked and judged. According to the calculated $D(i,j,t)$, select the appropriate threshold Y to judge each pixel point in the image, and let:

$$I(i,j,t)=\begin{cases}0, D(i,j,t)<Y\\ 1, D(i,j,t)\geq Y\end{cases} \quad (6)$$

For the pixel points $I(i,j,t)$ is 0, the pixel points $I(i,j,t)$ is 1 are the candidate suspect targets, so the clutter in the background can be removed, leaving the moving target points and a small part of the residual noise points. The number of suspect candidate points of moving target can be greatly reduced by segmentation of pixel points with drastic change in gray level, which makes it possible to further segment the real moving point targets. For the suspicious target, according to its motion continuity and consistency, it can be further eliminated by optical flow method, multi-frame energy cumulative average method, etc., so as to detect the real moving target.

When the displacement of the moving point target between adjacent frames is not less than one image element, the order is taken in the partial derivative vector; when the displacement of the moving point target between adjacent frames is less than one image element, the differential time spacing can be lengthened until the displacement of the point target in the two differential frames is not less than one image element, and for the point target whose displacement between adjacent frames is not less than 1/2 image element, the order is taken to complete the detection, and for the point target whose displacement between adjacent frames is not less than 1/2 image element, the order is taken to complete the detection. For the point target whose displacement between adjacent frames is not less than 1/3 of an image element, the detection can be completed by taking. After detecting the tennis ball in the tennis serve training video, the trajectory of the tennis ball in the image is tracked using the Mean Shift algorithm.

1.3 Tracking tennis ball movement using the Mean Shift algorithm

MeanShift algorithm is a non-parametric density estimation and has an important position in the target tracking algorithm because of its high real-time performance. When MeanShift algorithm is applied to target tracking, the first step is to characterize the target and the candidate target, establish the target model and the candidate target model, compare the similarity between the two models by using the baroclinic coefficient, and obtain the possible position of the target in the next frame by combining the baroclinic coefficient and the mean vector. The MeanShift algorithm converges quickly and if iterative steps are performed repeatedly, it will eventually converge to the correct position of the target and complete the whole target tracking process [15].

The MeanShift tracking algorithm models the target to be tracked in terms of a feature histogram, which is called the target model. The MeanShift target tracking algorithm is semi-automatic and the tracking process starts by manually selecting the target or setting the target start

parameters, and the width of the selected region is the kernel window width h. The pixel feature space of the selected region is counted. The feature space can be color, texture, contour, etc. The probability density expression of the target model can be given in the following form [16].

$$q_u = C\sum_{i=1}^{n} K\left(\left\|x_i^*\right\|^2\right)\delta\left[b\left(x_i - u\right)\right] (7)$$

In formula (7), $b\left(x_i\right)$ is the eigenvalue of the pixel at sample point x_i; $\delta\left(x\right)$ is the Delta function; u is the histogram feature index of tennis sports image; K is the kernel function of MeanShift algorithm; x_i^* is the pixel position of the image after normalized processing; C is the standardized constant coefficient. In the calculation of the target model, $\delta\left[b\left(x_i\right)-u\right]$ is used to determine whether the characteristic quantization value of each pixel in the image is u. If the corresponding value is u, then $\delta\left[b\left(x_i\right)-u\right]$ takes the value of 1. If the corresponding value is not u, then $\delta\left[b\left(x_i\right)-u\right]$ takes the value of 0.

The region in the sequence image that may contain the tracking target is usually called the candidate target region, and its center is defined as y, and the candidate target model is calculated with y as the center. The pixels in the candidate target region are denoted by $\left(x_i\right)$, then the probability density expression of the candidate target template is [17-18].

$$p_u\left(y\right) = C_h\sum_{i=1}^{n} K\left(\left\|\frac{y-x_i}{h}\right\|^2\right)\delta\left[b\left(x_i\right)-u\right] (8)$$

In formula (8), h is the size of the initial frame area, namely the kernel window width; y is the candidate target center location; C_h is the standardized constant coefficient. Window width h affects the distribution of weight. The other parameters have the same meaning as those in the probability density expression of the target model.

The MeanShift target tracking algorithm uses the Bhattacharyya coefficient as a criterion for judging the similarity between the models, and the larger the Bhattacharyya coefficient, the more similar the target is to the candidate target. The formula for calculating the Bhattacharyya coefficient is given in the following equation.

$$\rho\left(p,q\right) = \sum_{u=1}^{m}\sqrt{p_u\left(y_0\right)q_u} \ (9)$$

The target model and the candidate target model in equation (9) are both normalized n-dimensional vectors. the MeanShift tracking algorithm continuously compares the baroclinic coefficients of the target model and the candidate target model through iterations to determine the moving direction of the search window and obtain the correct position of the target. From the principle of MeanShift algorithm, it is known that to search the target region in the current frame image, it is necessary to determine the target position in its neighborhood with the position y_0 of the target in the previous frame image as the starting position. The first-order linear approximation

of $\rho(p,q)$ can be obtained by expanding the Barclay's coefficients in the neighborhood of y_0 and omitting the higher-order terms, and its expression is shown as follows.

$$\rho\left[p(y),q\right] \approx \frac{1}{2}\sum_{u=1}^{m}\sqrt{p_u(y_0)q_u} + \frac{1}{2}\sum_{u=1}^{m} p_u(y_0)\sqrt{\frac{q_u}{p_u(y_0)}} \quad (10)$$

Substitution of the candidate target expression into the above equation and analysis shows that the new position of the moving target is related to the $\rho\left[p(y),q\right]$ taken values. Using the mean offset vector to calculate the extreme value point of the density estimate in the neighborhood of point y_0, the expression for the center of the target region moving from y_0 to the new position y_1 is as follows [19].

$$y_1 = \frac{\sum_{i=1}^{n} x_i w_i g\left(\left\|\frac{y_0 - x_i}{h}\right\|^2\right)}{\sum_{i=1}^{n} w_i g\left(\left\|\frac{y_0 - x_i}{h}\right\|^2\right)} \quad (11)$$

In equation (11), w_i is the weighting coefficient. In the Mean Shift algorithm, the first-order Talor expansion of the correlation matching function of the target model and the candidate model is used to approximate and find the next target position of the iteration, so as to determine the new position of the moving target, and after determining the position of the tennis ball in the video image according to the above equation, the Kalman filter is used to perform the best sharp tangent based on the tracking information of the Mean Shift algorithm point prediction.

1.4 Complete the sweet spot prediction

The position of the target in each frame of the tennis ball hitting scene constitutes the trajectory of the tennis ball moving in the air, and the Kalman filter is introduced to predict the possible position of the tennis ball in the current frame based on the information of the position points of the tennis ball in the past. Therefore, the state variables and observations in the Kalman filter are the position information of the tennis ball, or more precisely, the information related to the coordinates of the center of the tennis ball being tracked. In order to break the limitation of the use of Kalman filter algorithm and make it applicable to nonlinear systems, the nonlinear system equations can be linearized and approximated, and then the approximated results can be used for Kalman filtering, from which the extended Kalman filter algorithm is derived. The extended Kalman filter algorithm, which linearizes the approximation of nonlinear functions using Taylor series expansion, is one of the most commonly used suboptimal estimation methods to deal with weakly nonlinear systems. The following dynamic system is developed [20-21].

$$\begin{aligned} x_k &= f(x_{k-1}, u_k) + w_k \\ z_k &= h(x_k, u_k) + v_k \end{aligned} \quad (12)$$

In formula (12), $f\left(x_{k-1},u_k\right)$ is the kalman filter prediction function; $h\left(x_k,u_k\right)$ is the observation function of Kalman filter; w_k is state noise of Kalman filter; v_k is the observation noise of Kalman filter; u_k is the control quantity, and the control quantity without input can be set to 0; x_k is the state vector of Kalman filter at time k; z_k is the observation vector of Kalman filter.The extended Kalman filtering algorithm linearizes the nonlinear system equation by using Taylor expansion. In the process of approximation, the higher order terms above the second order are omitted and only the first derivative part is retained. The computation of Jacobian matrix is complex and the real-time performance is poor. Moreover, the linearization of the nonlinear system equation in the extended Kalman filter algorithm only retains the first derivative, which is easy to cause truncation error for the strongly nonlinear system. To solve the above problems, the Jacobian matrix is replaced by the difference linearization method for the state estimation and error variance of Kalman filter.

The figure 1 is a diagram of tennis player's service action. The mark points in the figure are service marks.

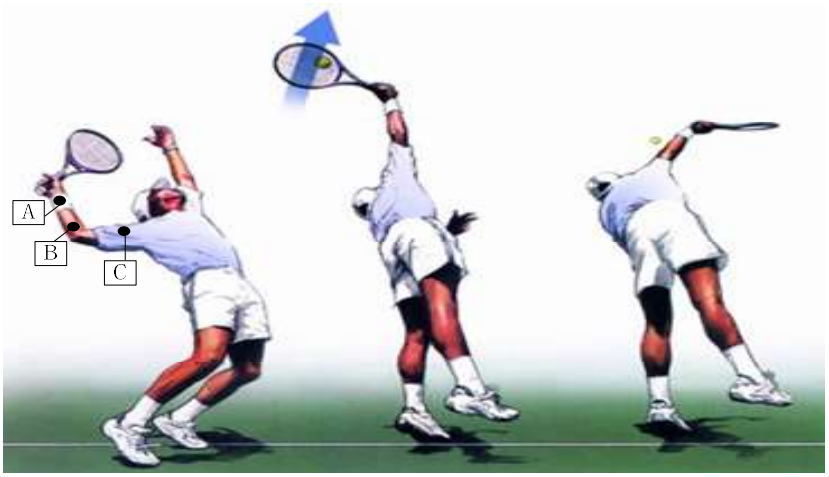

Figure 1 Schematic diagram of service action and service arm markers

The marker points in the diagram above have no effect on the player's serve. Point A represents the marker point at the wrist near the racket, point B represents the marker point at the elbow, and point C represents the marker point at the serving arm near the shoulder. The throwing arm should be fully extended and the ball should be thrown slightly in front of the body. The height of the ball should be about the same as the height of the head. A reasonable height of the ball from the hand will make the ball's path more stable after the ball is thrown. If the height of the ball is too low, it will shorten the control distance of the ball, thus weakening the control of the ball, which is not conducive to the acceleration of the ball and does not allow the player to control the direction of movement after the ball is thrown. Studies have shown that the higher the hitting point, the greater the success rate of the serve and the maximum speed generated. After the racket hits the ball, the ball will move parabolically with initial velocity. Therefore, the higher the speed of the ball after hitting, the shorter the time for the opponent to react; the higher the hitting point, the

greater the possibility of the ball passing the net, while the opposite will increase the difficulty of the hitting action and make the ball easily hit the net, leading to the failure of the serve. Based on the template parameters of the best hitting point for different players, the Kalman filter is used to predict the best hitting point for tennis balls. Through the above steps, the obtained hitting point position is the best hitting point for the player's tennis serve. This completes the study of the optimal hitting point prediction method for tennis serves based on the Mean Shift algorithm.

2 Case validation study

For tennis players, the quality of the receive-serve session plays a decisive role. The best hitting position is different when the route, angle and rotation direction of the incoming ball are different. Predicting the best hitting point position can reduce the processing time of return information, find the correct stance as fast as possible, ensure the quality of receiving and serving, and facilitate the offense and defense. The above paper studied the method of predicting the best hitting point of tennis serve based on the Mean Shift algorithm, and in this section, specific experimental steps are designed to verify the effectiveness of this prediction method for experimental testing.

2.1 Experimental environment setup

To ensure the real validity of the experimental results, all experiments were conducted in the same experimental environment. For the hardware environment, we use Intel core i7 4790 CPU, 8GB memory, 36GB SCSI hard disk, and 1000mb/s internal adaptation for the network card. For the software environment, the software development is done under Windows 8 operating system and the integrated development environment is Visual Studio 2013. in this section, Visual Studio 2013 and Opencv2.4.9 are used to process the captured tennis serve video.

2.2 Experimental procedure

The experiments were conducted in the form of comparison experiments, using the scientific and intuitive nature of comparison experiments, by comparing the traditional best hitting point prediction method as a comparison item with the studied best prediction method for hitting point, and judging the performance advantages and disadvantages of the prediction method in this study based on the comparison differences between the experimental data.

The best hitting point prediction method of serve mentioned in literature [2] and literature [4] were chosen as the comparison method for this experiment and the best hitting point prediction method of tennis serve based on Mean Shift algorithm studied in this paper. The three hitting point prediction methods are loaded into the same simulation platform, and the experimental variables are controlled uniquely to complete the experimental validation. The error between the prediction results of the prediction methods and the theoretical optimal hitting point and the time consumed by the three methods to calculate the optimal hitting point were selected as the comparison parameters for this experiment.

Ten tennis players with different body sizes were invited to participate in this experiment, and a high-speed camera was used to capture the video of 10 tennis players' serves as the data set for the three best hitting point prediction. Physical fitness and physical quality tests were conducted on the 10 tennis players, and theoretical models were established based on the test results to

calculate the optimal hitting point positions corresponding to the 10 players' motion parameters. The errors between the prediction results of the three prediction methods and the theoretical values were calculated, and the calculation time consumed by the three methods for the best hitting points of different players' serves was recorded. Comprehensive comparison of the experimental data corresponding to the above two experimental indexes leads to the final conclusion of this experiment and completes the experimental validation.

2.3 Experimental results

In this experiment, the experimental data of the three methods of predicting the best hitting point of serve for 10 players are shown in the following table. The data in the table were compared and the corresponding experimental conclusions were obtained by further processing of the data in the table 2.

Table 2 Comparison of experimental data

Serial number	Research methods			Methods in literature [2]			Methods in literature [4]		
	Error value /cm		Predicted elapsed time /s	Error value /cm		Predicted elapsed time /s	Error value /cm		Predicted elapsed time /s
	X	Y		X	Y		X	Y	
1	0.300	0.277	1.24	0.813	0.769	4.88	0.566	0.576	3.84
2	0.286	0.290	1.22	0.819	0.802	4.73	0.581	0.563	3.86
3	0.284	0.296	1.27	0.736	0.737	4.72	0.568	0.589	4.35
4	0.292	0.301	1.25	0.795	0.734	4.75	0.572	0.574	3.84
5	0.275	0.292	1.36	0.752	0.748	4.84	0.567	0.562	4.12
6	0.272	0.298	1.22	0.747	0.819	4.79	0.564	0.586	4.30
7	0.296	0.277	1.34	0.798	0.756	4.85	0.579	0.574	4.41
8	0.293	0.285	1.28	0.783	0.751	4.66	0.566	0.578	4.36
9	0.298	0.304	1.32	0.809	0.791	4.73	0.578	0.582	4.33
10	0.281	0.273	1.30	0.818	0.741	4.71	0.573	0.585	4.20

From the above table, it can be seen that the experiments consumed by the method in this paper for prediction are much less than the other two groups of methods, which indicates that the method in this paper is more efficient in the search for the optimal processing. Analysis of the prediction error data of each prediction method in the above table shows that the errors of the hitting point prediction methods studied in this paper are much smaller in X and Y directions than the methods mentioned in the literature [2] and literature [4], and the prediction errors of the methods mentioned in the literature [4] are slightly smaller than the methods mentioned in the literature [2] in comparison. The average error of the three methods in this experiment is 0.288 cm in the X direction and 0.289 cm in the Y direction; the average error of the method of [2] is 0.787 cm in the X direction and 0.765 cm in the Y direction; the average error of the method of [4] is 0.572 cm in the X direction and 0.572 cm in the Y direction. Based on the above data, the average improvement of the prediction accuracy of the method in this paper is at least about 50%.

In conclusion, the method of predicting the best hitting point of tennis serve based on the Mean Shift algorithm in this paper has high prediction accuracy and efficiency, which can help improve the players' serving ability and has practical use.

3 Conclusion

The best hitting point can make the player get the best hitting power, speed, and effectively control the line of serve and the drop point of the serve with the least cost of joint movement. The strength of the player's ability to predict the best hitting point position can reflect the level of his or her skill, and this ability is accumulated and improved during daily training. Therefore, a high-precision and high-efficiency method for predicting the best hitting point of tennis serve can facilitate players and coaches to obtain and analyze the corresponding best hitting point positions of different players, and improve their ability to predict the best hitting point positions and tennis skills. To this end, this paper investigates the optimal hitting point prediction method for tennis serves based on the Mean Shift algorithm. It is verified through simulation experiments that the prediction method studied in this paper has higher accuracy and better performance.

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